THE POLLUTION EFFECTS OF MERGERS AND ACQUISITIONS: ASYMMETRY AND SECTOR DISAGGREGATION

by

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ABSTRACT

SIMON KIRKEGAARD HOLST. The Pollution Effects of Mergers and Acquisitions: Asymmetry and Sector Disaggregation. (Under the direction of DR. PAUL GAGGL)

This paper investigates the relationship between CO_2 emissions and cross-border mergers and acquisitions (M&A). It does so using country-level data on CO_2 emissions and cross-border transactions from the period 2000-2020. The paper focuses on two main aspects: asymmetry concerning income levels of both target and acquirer nations and sector-specific effects. First, the paper tests whether M&As from a high-income country (acquiring country) reduce CO_2 emissions. Second, it tests whether only M&A in polluting sectors affect CO_2 emissions. The main finding of the paper is that what matters for the impact of cross-border M&A on pollution is not where it is coming from but where it is going. M&A going to a high-income country reduces emissions while M&A going to a low-income country increases emissions. Furthermore, the paper finds mixed evidence of sector-specific effects which calls for further research and rethinking of sector disaggregation.

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CHAPTER 1: INTRODUCTION

The economy and the environment are indisputably intertwined. It is a relationship that is receiving increasingly more attention from economists due to the environmental challenges the world is facing. To tackle climate change it is essential that we understand the relationship between pollution and economic factors such as trade, growth, and foreign direct investment (FDI). Climate change is a challenge that transcends borders while the world is getting more and more globalized. It is therefore crucial that we understand the impact FDI has on pollution. The literature has primarily treated FDI as an overall factor. However, there is good reason to consider the two components that make up FDI separately, namely mergers and acquisitions (M&A) and greenfield investments. The reason for this is twofold. First, cross-border M&A used to dominate the value of global FDI from the 1990s up until the financial crisis, after which greenfield investments started to drive FDI flows. In recent years, however, M&A has made a comeback. As Figure 1.1 shows, the number of cross-border M&A transactions may be considerably lower than greenfield project but the value of cross-border M&A is very close to that of greenfield projects. Second, the nature of M&A and greenfield investments is very different regarding their environmental impact. Greenfield investments refer to the construction of new facilities while M&A is the acquisition of already existing facilities. Firms that invest in greenfield projects start from scratch which allows them to build their facilities exactly as they like. Firms engaging in M&A find themselves facing a more complex choice, namely whether to use existing facilities as they are or adopting new technologies. This decision may determine whether cross-border M&A has a positive or negative impact on pollution in the target country.

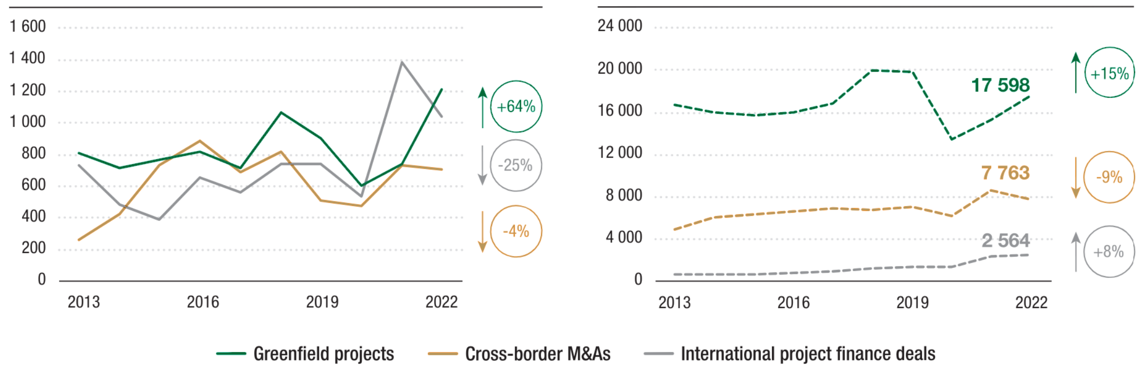

Figure 1.1: Value (left) and number (right) of announced greenfield projects, international project finance deals and cross-border M&As, 2013-2022 (Billions of dollars, number and percent). Source: UNCTAD World Investment Report 2023

This paper investigates the impact of cross-border M&A on CO_2 emissions and the factors that determine the impact. It does so by considering $fromwhere$ and $whereto$ M&A is flowing, and to what sectors M&A is flowing. I find that it is not where M&A is coming from that the determines its impact on pollution but rather where it is going to. M&A flowing to high-income countries has a low or even negative impact on CO_2 emissions while M&A flowing to low-income countries has a positive impact on CO_2 emissions. Furthermore, I find that in addition to M&A in the Pollution-Intensive sector, M&A in Construction & Service has an impact on pollution. This suggests that a spill-over effect exists.

To understand the underlying mechanisms of the impact of M&A on pollution, we need to consider where M&A flows are coming from and where they are going. High-income countries are associated with higher environmental standards and cleaner technologies than what we experience in low-income countries. It is therefore likely that the income level of the acquiring firm's home country and the income level of the target country matter for the environmental impact of M&A. Another component in the mechanism that is relevant to consider is the sector of the target firm. Given that some sectors pollute more than others, it is reasonable to expect that the impact of

M&A on pollution depends on the target sector.

To investigate the impact of cross-border M&A on pollution, I focus on the main anthropogenic greenhouse gas, Carbon Dioxide (CO_2) in this paper. I investigate the relationship between M&A and CO_2 emissions by testing two hypotheses.

1.1 Hypotheses

Hypothesis 1:

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

Given that multinational firms from high-income countries often face stricter environmental regulations, we should expect that they implement cleaner technologies when acquiring firms abroad than multinationals from low-income countries. Thus, I test whether there is an asymmetric relationship.

Hypothesis 2:

- Sector-specific impact: Only M&A in polluting sectors affect CO_2 emissions.

Given that pollution intensity differs across sectors, we should expect different point estimates across sectors. Thus, I test whether M&A flows only have an impact on the environment in pollution-intensive sectors.

I utilize transaction and country-level data from 2000-2020 to test the hypotheses stated above. The paper is organized as follows. First, I review the literature that has motivated this paper. Second, I describe the data and present the summary statistics. Third, I explain the empirical model I use to test the three hypotheses. Fourth, I present the results and discuss the implications. And finally, I conclude.

CHAPTER 2: LITERATURE REVIEW

The model I test is motivated by theoretical as well as empirical literature. First, I review the theoretical literature that motivates the three hypotheses of this paper. This literature covers the characteristics of multinationals that engage in M&A and how innovation affects pollution. Second, I review the literature on M&A and its environmental impact. The literature is very limited, hence I also cover studies that look into the relationship between FDI and the environment in general.

2.1 Theoretical motivation

The theory presented by Neary (2007) shows that acquiring firms are the most efficient among their competitors. This is supported empirically by Brakman et al. (2005). In addition to that, several papers show that these acquiring multinationals are innovating to a greater extent than their uni-national peers. These are important findings because they suggest that multinationals are more likely to reduce costs, use higher-quality products, and run cleaner processes. Linking the literature presented above to the findings of Porter and van der Linde (1995) is interesting because they show that innovation can lead to a reduction in pollution. They explain this by showing that firms that face higher environmental standards have higher incentives to develop cleaner products and processes. Similarly, Qiu et al. (2020) show that environmental regulation pressures firms to conduct green process innovation. The results of the papers presented here suggest that firms active in M&A from high-income countries should have the incentives and capacity to adopt cleaner technologies and pollute less.

2.2 Empirical evidence

In recent years, the environmental agenda has received much greater attention than previously. One of the papers focusing on the relationship between M&A and the environment, and a paper which inspired this paper, is one by Swart and van Marrewijk (2011) which studies the impact of cross-border M&A on CO_2 emissions and finds that the development level of the target country determines the direction of the effect of M&As on CO_2 emissions, that only pollution-intensive sectors have an impact on CO_2 emissions, and that multilateral agreements are important in reducing CO_2 emissions. Similarly, Ashraf et al. (2021) look at both M&A and greenfield investments, but separately. They too find that M&A flowing to developed countries reduces pollution while greenfield investments in developing countries increase pollution. Chandrika et al. (2022) conclude that India is in danger of becoming a pollution-haven for multinationals undertaking cross-border M&A and argue that policies ensuring knowledge spillover rather than offshoring of emissions are needed. Recently the M&A literature has started focusing on "green M&A". In contrast to the focus of this paper, green M&A refers to the situation where the acquiring firm takes over another firm to acquire cleaner technology that will make the multinational as a whole more environmentally friendly. X. Liang et al. (2022) take a resource-based perspective and show that green M&A by heavily polluting enterprises can promote green innovation, and that this impact is promoted with the support of government subsidies.

Despite the papers mentioned above, the current literature tends to focus on FDI as a whole rather than considering M&A and greenfield investments separately. Using panel regression analysis, Jorgenson (2007a) finds that FDI dependence positively impacts CO_2 and organic water pollutants in the manufacturing sector for less developed countries. In another paper, Jorgenson (2007b) shows that FDI dependence in the agriculture sector increases CO_2 emissions for less developed countries. F. H. Liang (2008) uses sulfur dioxide as a measure for pollution in China and, interestingly, finds that SO_2 decreases with FDI. Bao et al. (2008) take a different approach and use data from China to show that FDI from multinationals initially increases pollution in the target country but after a certain threshold, it reduces pollution because as more multinationals enter, the demand for environmental regulation goes up.

The literature has also considered the impact of trade openness on the environment. Frankel and Rose (2005) find a positive relationship between trade openness and CO_2 emissions. They suggest that the reason for this could be that target countries do not attempt to reduce their emissions for fear of losing competitiveness. In contrast, Harbaugh et al. (2002) and Antweiler et al. (2001) find a negative relationship between trade openness and SO_2 emissions.

This review of the current literature shows several gaps and motivates the research of this paper. First, I believe the current literature fails to recognize the importance of separating M&A from greenfield investments given that the two are very different in nature. Greenfield investments involve the construction of completely new facilities, while M&A only entails the acquisition of already existing facilities. This paper therefore focuses exclusively on M&A. Second, given what we already know about acquiring firms, innovation, and environmental standards, it is relevant to investigate whether there is an asymmetry between high-income and low-income countries in regard to the impact of M&A on pollution. Third, since the degree of pollution differs greatly from sector to sector, we need to consider how sectors matter for the relationship between M&A and pollution. This paper therefore tests in which sectors M&A affects pollution.

CHAPTER 3: DATA

To capture pollution effects I use carbon dioxide emissions as my dependent variable. My final dataset includes emissions data stemming from the burning of fossil fuels and the manufacture of cement from 158 countries. Emissions are measured in metric tons and the data comes from World Bank. There are good reasons to choose carbon dioxide emissions as the dependent variable. First, it is available annually for many countries which makes the coverage better than for other air polluters such as SO_2 and NO_x. Second, it is a major anthropogenic greenhouse gas that accounts for a great deal of global warming (Swart & van Marrewijk, 2011).

I also use the World Bank to collect relevant control variables. Those control variables include GDP, GDP per capita, population, urban population, manufactures export, manufactures import, manufacturing (value added), and trade. To account for inflation, I use GDP and GDP per capita in constant 2015 USD. Population is in absolute numbers while urban population is measured as a fraction of the total population. Manufactures exports and imports are in fractions of merchandise exports and imports, respectively. Finally, manufacturing and trade are measured in percentage of total GDP. I will justify the choice of these control variables later. In addition to the control variables, I also extract GNI per capita from the World Bank which is used to classify countries' income levels.

I collect data on M&A transactions using the Dealscreener-tool by Refinitiv Workspace. I consider all cross-border transactions that were completed within the period 2000-2020. This resulted in 213,130 transactions initially. Some transactions included target countries that are not considered countries by the World Bank which meant that some transactions had to be dropped. After this step, I was left with 210,963 transactions. These transactions were all grouped into four sectors based on the SIC industry of the target company (see Table 3.1). To measure M&A activity, I consider two alternative measures, deal value and target LTM (last twelve months) sales. I construct the annual M&A flow variables by summing up deal value/LTM sales of all transactions within a given year and group by sector and target country.

After merging the data from the World Bank and Refinitiv Workspace and removing all incomplete observations, the dataset includes 2,808 observations for 158 countries. See Appendix A for a detailed description of how the data was retrieved and treated. Table 3.2 provides an overview of the data sources I used to construct my variables.

Table 3.1: Sector disaggregation (non-exhaustive)

Sector group	**Representative sectors**
A - Agriculture and Mining	Agriculture; Forestry; Fishing and Mining
C - Construction and Service	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: The disaggregation follows the one made by Swart and van Marrewijk (2011) who uses the ratio of kilograms of Carbon Monoxide Emission over the value of output, from the Industrial Pollution Projection System.

Table 3.2: Data sources

Variable	Definition	Source	Period
CO_2	Emissions (metric tons)	World Bank	2000-2020
M&A inflow	Deal value	Refinitv Workspace	2000-2020
M&A inflow	Last 12 months sales	Refinitv Workspace	2000-2020
Population	Number of residents	World Bank	2000-2020
GDP	Constant 2015 USD	World Bank	2000-2020
Manufacturing	Value added (% of GDP)	World Bank	2000-2020
Urban	Urban population (% of total)	World Bank	2000-2020
Manufactures exports	(% of merchandise exports)	World Bank	2000-2020
Manufactures imports	(% of merchandise imports)	World Bank	2000-2020
GDP per capita	Constant 2015 USD	World Bank	2000-2020

CHAPTER 4: SUMMARY STATISTICS

The deal value of an M&A transaction is not always made public which is why data on M&A deal values is limited. What is crucial for this paper is that we do not see major differences in the fraction of transactions with missing deal values or target LTM sales across years or sectors. Table 4.1 shows the number of transactions by year and the number of transactions with deal value and target LTM sales. The fraction of transactions with deal value and target LTM sales is fairly stable across time. The average fraction of transactions with deal value available is 40%. In the years with the lowest and highest data availability, the fraction is 34.8% and 46.2%, respectively. For target LTM sales the average fraction of transactions with available data is 21.5% with the lowest and highest fraction being 17.1% and 27.2%, respectively. The fraction of transactions with deal values or target LTM sales available is not as stable when we look across sectors, especially not when considering deal value. Table 4.2 shows that 60.1% of the transactions within Agriculture & Mining have deal values available while only 38.9% of the transactions within the Medium Pollution Intensive sector have deal values available. We see a bit more stability when considering transactions that have target LTM sales available. 28.4% of the transactions within the High Pollution Intensive sector have target LTM sales available while 19.2% of the transactions within Construction & Services have target LTM sales available. It should be noted that the transactions within the Undefined category will not be included in the regressions later on as it was not possible to assign them to a sector. Tables 4.1 and 4.2 also provide information about how the transactions in general spread across time and sectors. From Table 4.1 we can tell that the number of transactions has gone up and down in the period 2000-2020 with the peaks being around

2007 and 2018. Table 4.2 shows clearly that the vast majority of the transactions have been in Construction & Services while the Medium Pollution Intensive sector comes in second with less than a third as many transactions.

Since the regressions of this paper will be based on M&A inflow measured in deal value or target LTM sales, however, we must look at the statistics based on these measures rather than the number of transactions. Tables 4.3 and 4.4 report summary statistics grouped by sector based on deal value or target LTM sales, respectively. The pattern is the same. Construction & Service account for the majority of M&A activity. Around 60% of total M&A activity is in Construction & Service which is similar to what was the case when looking at the number of transactions. In general, each sector's share of total M&A activity seems to be the same regardless of whether we use frequency, deal value, or target LTM sales as the measure. Tables 4.3 and 4.4 also provide intel about the size of the transactions in each sector. First, if we look at Table 4.3 it seems that deals within the Pollution Intensive sectors are bigger on average but also that the size of the deals varies more. Second, from Table 4.4 we can tell that average target LTM sales are much higher for targets in the High Pollution Intensive sector and that target LTM sales vary much more for targets in Agriculture & Mining. Still, we should remember that the number of observations in each sector differs a lot which makes comparison across sectors less reliable.

A final disaggregation of the data I made is shown in Table 4.5. Here I present the fraction of total deal value and target LTM sales, respectively, by sector, and by income-level of target country as well as acquirer country. It shows that almost half of the M&A activity happens between high-income countries in Construction & Service. In general, we see that roughly 75-80% of M&A activity is between high-income countries. The Medium Pollution Intensive sector is the sector with second-highest activity-level, and this is again driven by transactions between high-income countries.

Table 4.1: Transactions by year; 2000-2020

Year	**Total Deals**		**Deals with Value**		**Deals with LTM Sales**	
	Frequency	**(%)**	**Frequency**	**% of sector**	**Frequency**	**% of sector**
2000	10,585	5.0	4,542	42.3	2,847	26.9
2001	8,118	3.9	3,536	43.6	2,210	27.2
2002	6,176	2.9	2,788	45.1	1,249	20.2
2003	6,287	3.0	2,824	44.9	1,078	17.1
2004	7,164	3.4	3,307	46.2	1,415	19.8
2005	8,769	4.2	3,885	44.3	1,629	18.6
2006	10,262	4.9	4,418	43.1	2,044	19.9
2007	12,552	5.9	5,428	43.2	2,769	22.1
2008	11,671	5.5	4,767	40.8	2,752	23.6
2009	8,270	3.9	3,346	40.1	1,775	21.5
2010	10,062	4.8	4,149	41.2	2,001	19.9
2011	10,784	5.1	4,403	40.8	2,186	20.3
2012	9,968	4.7	4,003	40.2	2,351	23.6
2013	9,007	4.3	3,481	38.6	2,192	24.3
2014	10,139	4.8	3,935	38.8	2,393	23.6
2015	11,173	5.3	4,172	37.3	2,689	24.1
2016	11,630	5.5	4,045	34.8	2,540	21.8
2017	12,280	5.8	4,534	36.9	2,661	21.7
2018	12,554	6.0	4,521	36.0	2,249	17.9
2019	12,381	5.9	4,358	35.2	2,119	17.1
2020	11,131	5.3	4,137	37.2	2,107	18.9
Total	210,963	100.0	84,579	40.0	45,256	21.5

Table 4.2: Transactions by sector; 2000-2020

Sector	**Total Deals**		**Deals with Value**		**Deals with LTM Sales**	
	Frequency	**(%)**	**Frequency**	**% of sector**	**Frequency**	**% of sector**
Agriculture and Mining	15,049	7.1	9,044	60.1	3,332	22.1
Construction and Service	134,246	63.6	51,068	38.0	25,830	19.2
Zero Pollution Intensive	13,244	6.3	5,415	40.9	3,477	26.3
Medium Pollution Intensive	41,339	19.6	16,092	38.9	10,620	25.7
High Pollution Intensive	6,412	3.0	2,690	42.0	1,818	28.4
Undefined	673	0.3	270	40.1	179	26.6
Total	210,963	100.0	84,579	40.0	45,256	21.5

Table 4.3: Summary statistics of deal value by sector group.

Sector	Mean	SD	Max.	Sum	% of Total Value
Agriculture and Mining	190.0	799.0	19,123.0	1,717,357.0	9.0
Construction and Service	216.0	1,404.0	202,744.0	11,029,661.0	58.1
Zero Pollution Intensive	196.0	1,200.0	46,695.0	1,059,148.0	5.6
Medium Pollution Intensive	258.0	1,731.0	101,491.0	4,159,637.0	21.9
High Pollution Intensive	299.0	1,405.0	37,623.0	803,614.0	4.2
Undefined	792.0	3,651.0	49,054.0	213,723.0	1.1
All Transactions	224.0	1,424.0	202,744.0	18,983,141.0	100.0

Table 4.4: Summary statistics of target LTM sales by sector group.

Sector	Mean	SD	Max.	Sum	% of Total Value
Agriculture and Mining	859.0	11,634.0	562,427.0	2,861,232.0	8.0
Construction and Service	827.0	6,213.0	332,020.0	21,364,695.0	59.4
Zero Pollution Intensive	422.0	6,668.0	369,379.0	1,467,923.0	4.1
Medium Pollution Intensive	697.0	5,505.0	221,114.0	7,399,010.0	20.6
High Pollution Intensive	1,450.0	7,864.0	262,014.0	2,635,824.0	7.3
Undefined	1,272.0	3,609.0	22,768.0	227,638.0	0.6
All Transactions	795.0	6,715.0	562,427.0	35,956,323.0	100.0

Table 4.5: Transactions by sector and by income level of both acquirer and target countries; 2000-2020

Sector	% of total deal value					% of total LTM sales value				
Acquiring country	**High**		**Low**			**High**		**Low**		
Target country	**High**	**Low**	**High**	**Low**	**Total**	**High**	**Low**	**High**	**Low**	**Total**
Agriculture and Mining	5.3	1.8	0.9	1.1	9.0	4.2	3.2	0.2	0.4	8.0
Construction and Service	46.2	6.7	2.3	2.6	58.1	46.0	6.1	5.3	1.9	59.4
Zero Pollution Intensive	5.1	0.3	0.2	0	5.6	3.7	0.2	0.2	0	4.1
Medium Pollution Intensive	18.7	1.5	1.1	0.6	21.9	15.7	2.3	2.1	0.5	20.6
High Pollution Intensive	3.2	0.5	0.3	0.3	4.2	4.9	1.5	0.6	0.4	7.3
Undefined	1.0	0.1	0	0	1.1	0.6	0	0	0	0.6
Total	79.5	10.9	4.8	4.6	100.0	75.1	13.3	8.4	3.2	100.0

Below in Table 4.6, I present summary statistics for country-level variables retrieved from the World Bank. We can observe a high skewness for CO_2 emissions, GDP, GDP per capita, population, and trade openness. This led to the decision to take logs of these variables before running the regressions. In addition to that, it is convenient to take logs to allow for easier comparison. This will also be reflected later on in the empirical model. As for the rest of the variables, I leave them as they are.

Table 4.6: Summary statistics of variables

Variable	**Mean**	**Median**	**Standard Deviation**	**Skrewness**
CO_2	206,552	19,001	853,534	8.5138431
GDP	467,592,300	46,508,950	1,718,616,000	7.8432725
GDP_{pc}	14,573	5,813	18,949	1.9838875
$Population$	43,881,790	9,215,690	153,824,600	7.3912815
$Trade\,openness$	87.7991	77.97079	51.11365	2.5219604
$Manufacturing\,(\%\,GDP)$	13.36496	12.82971	6.351813	0.9779763
$Manufactures\,exports$	44.41213	44.91087	31.17842	0.4510632
$Manufactures\,imports$	65.14118	65.98897	11.50931	-0.6466988
$Urban\,population$	59.80773	61.57450	22.13432	-0.2741154

CHAPTER 5: EMPIRICAL MODEL

This paper seeks to test two main hypotheses:

- Hypothesis 1: M&As from a high-income country (acquiring country) reduce CO_2 emissions.
- Hypothesis 2: Only M&As in polluting sectors affect CO_2 emissions

To test these hypotheses I run a panel regression model with the specification:

$$Ln(CO_{2,it}) = \alpha_i + Ln(M_{it}^{'})\delta + Ln(M_{it}^{*'})\delta^{*} + C_{it}^{'}\pi + \varepsilon_{it} \tag{5.1}$$

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.

The dependent variable in this regression is Carbon Dioxide (CO_2) emissions in logs. On the right-hand side, we have three categories of variables. $Ln(M_{it}^{'})$ represents 8 variables that represent total M&A inflow (measured either by deal value or target LTM sales) in the four sectors separated by the income level of the acquiring companies' home countries. $Ln(M_{it}^{*'})$ represent 8 additional variables that are interactions between $Ln(M_{it}^{'})$ and the income level of the target nation (1 if the target nation is a high-income country, and 0 if not). Countries' income levels are based on their GNI per capita and the World Bank's historical classification. The World Bank uses the categories: high-income, upper-middle-income, lower-middle-income, and low-income. In this paper, I refer to high-income countries as high-income countries and all others as low-income countries. Both $Ln(M_{it}^{'})$ and $Ln(M_{it}^{*'})$ are in logs as the dependent variable to allow for easier interpretation. Thus, the δ's will show by how many percent emissions in a country change when the M&A inflow from low-income countries in a particular sector increases by 1% and the target nation is a low-income country. To get the effect when the target nation is a high-income country, we add the value of δ^* to δ. An example would be:

$Ln(M'_{P,HI,i,t})\delta_{P,HI} + Ln(M^{*'}_{P,HI,i,t})\delta^*_{P,HI}$

This notation implies that when cross-border M&A inflow in the Pollution Intensive sector from high-income countries goes up by 1%, emissions change by δ percent for low-income target countries and $\delta + \delta^*$ for high-income target countries.

Finally, we have C'_{it} which represents all the control variables in the panel regression. First, I include GDP or population as a control variable to take into account that higher GDP entails an economy with higher demand. Thus, more pollution is expected from countries with high GDP. Second, I include the urban population as a fraction of the total population to consider the fact that a lot of polluting activities take place in urban areas. Therefore, pollution is expected to be higher in countries with high urbanization. In addition to the scale component of growth which is taken into account by including GDP or population, I consider the technique and composition components of growth. Countries may use cleaner or dirtier technologies when they grow. To account for this I use GDP per capita as a proxy for countries' level of technique. I also include GDP per capita squared in my regressions. I add this quadratic effect to consider what has been labeled "the Environmental Kuznets curve". Grossman and Krueger (1991) developed this concept based on Simon Kuznets original Kuznets curve which shows the relationship between economic development and income-inequality. The Environmental Kuznets curve refers to a quadratic relationship between GDP per capita and CO_2 emissions. For low levels of economic development emissions increase while emissions decrease at high levels of economic development. Figure 5.1 plots this relationship. The quadratic effect is not that strong but it still suggests that it is worth considering in my regressions.

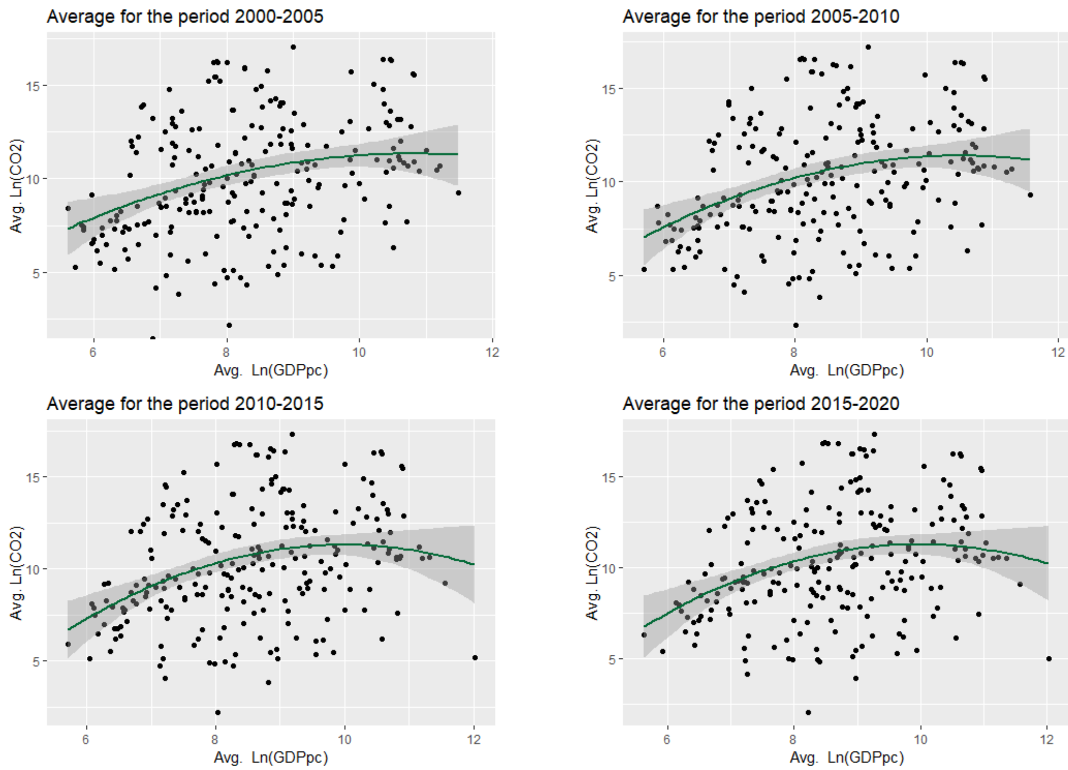

Figure 5.1: Environmental Kuznets curve: Country-level Ln(CO_2) vs. Country-level Ln(GDP per capita)

It is, however, also important to consider how countries' economic activity is composed. Countries that specialize in cleaner goods and services are expected to pollute less other things being equal. I account for countries' economic composition by including the value added of manufacturing as a percentage of the GDP. Finally, I also include the share of manufacturing exports, the share of manufacturing imports, and trade openness as control variables. I also interact trade openness with the income level of the target country to test the so-called "Pollution-Haven hypothesis". I test whether trade openness has a positive impact on pollution for low-income countries and a negative impact on pollution for high-income countries. The Pollution-Haven literature argues that this should be because of the strict environmental legislation in high-income countries compared to the more lax legislation in low-income countries.

CHAPTER 6: RESULTS

This part is split into two sections. The first presents the regression results where M&A inflows from year t have been used as the main regressors. The second presents the regression results where M&A inflows from year $t-1$ have been used instead. In both sections, I consider both deal value and target LTM sales measures for M&A inflow.

6.1 Regressions based on concurrent M&A inflows

The estimation results shown in Table 6.1 include four models. For models 1 and 2, the M&A inflow variables are based on deal value. For models 3 and 4, the M&A inflow variables are based on target LTM sales. Model 1 and 3 uses GDP to control for the scale effect of growth while models 2 and 4 use population. This setup will be the same for all the regression tables I present.

The first thing to notice in Table 6.1 is that all four models have high F statistics that are statically significant at a 99% level which indicates that the models do a good job in explaining country-level CO_2 emissions. The adjusted R-squared is approximately the same for the four models, around 0.63. The coefficient on trade openness is positive while it is negative when interacting with the income level of the target country. This supports the Pollution-Haven hypothesis. As for the rest of the control variables, the signs of the coefficients are as expected. Higher GDP, population, urban population, and income level are associated with higher pollution. The coefficient on GDP per capita is also positive but negative when squared. This is evidence for the Environmental Kuznet curve since it means that emissions increase when GDP per capita increases up until some point where emissions start to decrease with GDP per capita. This suggests that countries with low GDP per capita experience an increase in CO_2 emissions when growing while countries with high GDP per capita experience a drop in their emissions when growing, all else equal. While this makes high-income countries look good, we should note that the coefficients on the income-level dummy variable indicate that being a high-income country is associated with around a 100% increase in emissions.

Whether we use GDP or population to control for the scale effect of growth, the coefficients for the M&A inflows seem to stay the same. Thus, models 1 and 2 are much alike and so are models 3 and 4. However, when we compare the models based on deal value with the models based on target LTM sales, we see notable differences. Models 1 and 2 report a statistically significant positive effect from M&A inflows in Construction & Service going to low-income countries regardless of where it is coming from. The effect is stronger though when it comes from low-income countries. Low-income countries that experience a 1% in M&A inflows from other low-income countries in Construction & Service should experience a 0.007% increase in CO_2 emissions. We do not observe the same effect in models 3 and 4. These models, on the other hand, report a statistically significant positive effect from M&A inflows in the Pollution Intensive sector coming from low-income countries and going to low-income countries. The estimate implies that a 1% increase in M&A inflow from low-income countries in the Pollution Intensive sector will increase CO_2 emissions by 0.004% in low-income countries.

To see the estimated effect of M&A inflow on high-income countries, we need to add lines 9-16 to lines 1-8 in Table 6.1. Given that the majority of the coefficients in lines 9-16 are negative across all models, we can tell that M&A inflows in general have a lower impact on pollution in high-income countries than in low-income countries. The coefficients in lines 9-16 might even be negative enough to create an overall negative effect on pollution. That is indeed what we see in models 1 and 2 for the case of M&A inflows in Construction & Service going to high-income countries. When M&A flowing from high-income countries to high-income countries in Construction & Service increases by 1%, CO_2 emissions decrease by 0.006% $(0.003+(-0.009)$. When the money is coming from low-income countries, the effect is a 0.004% decrease $(0.007+(-0.011))$. Models 3 and 4 also report statistically significant negative effects when the target country is high-income. When M&A inflows from low-income countries in Construction & Service and in the Pollution Intensive sector increase, CO_2 emissions decrease in high-income countries. To sum up, the results so far indicate that M&A inflows in certain sectors have a positive effect on pollution in low-income countries and a negative effect on pollution in high-income countries. What sectors have significant effects depends on how M&A activity is measured. Models 1 and 2, which are based on deal value, find significant effects in Construction & Service regardless of where the inflows are coming from. Models 3 and 4, which are based on target LTM sales, find significant effects in the Pollution Intensive sector in particular, and only when the inflows are coming from low-income countries.

Table 6.3 takes a closer look at M&A inflows within the Pollution Intensive sector by disaggregating them into inflows in the Medium Pollution Intensive sector and the High Pollution Intensive sector. See Table 6.2 for the updated sector disaggregation. In general, the pattern in Table 6.3 is the same as in Table 6.1. However, we do see a difference when it comes to M&A inflows from low-income countries to high-income countries. The effects from inflows in the Medium Pollution Intensive sector seem to be negative across all models while we do not see any significant effects for inflows in the High Pollution Intensive sector. This is surprising but it is important to keep in mind the data availability. As mentioned earlier the data includes many more transactions in the Medium Pollution Intensive sector than in the High Pollution Intensive sector.

6.2 Regressions based on 1-year lagged M&A inflows

In this section, I present the regression models that are based on 1-year lagged M&A inflows. When companies acquire or merge with other companies it takes time for them to implement new measures. The acquirer may implement new cleaner technologies or reallocate dirty activities to the newly acquired company. In any case, it can be argued that we do not see the effect of an M&A transaction on pollution in the same year as the acquisition was made. In principle, the transaction could take place on December 31st in which case it probably wouldn't have any effect on the target country's annual emissions that year. Therefore, I use transactions happening in the year before to construct the M&A inflow variables.

Table 6.4 shows the regressions estimates for the lagged M&A inflow variables. The pattern resembles the one in the previous models. All models show evidence of high-income countries generally experiencing negative or at least less positive effects of M&A on CO_2 emissions whereas low-income countries generally experience positive or insignificant effects of M&A on CO_2 emissions. Again, the level of significance depends on the sector and what measure is used to capture M&A inflows.

As for the non-lagged regressions, I also present the estimates where the Pollution Intensive sector has been disaggregated in Table 6.5. The results resemble the ones we saw for the non-lagged disaggregated regression models. The effects are significant for M&A inflows in the Medium Pollution Intensive sector when the money is flowing from low-income countries to high-income countries but not in the High Pollution Intensive sector.

Table 6.1: Fixed Effects Models for CO_2 emissions: M&A inflows in concurrent year

	Dependent variable: $Ln(CO_2)$			
	Deal Value		Target LTM Sales	
	(1)	(2)	(3)	(4)
$Ln(M_{AM,HI})$	0.002	0.002	0.002	0.002
$Ln(M_{CS,HI})$	0.003^{**}	0.003^{**}	-0.001	-0.001
$Ln(M_{ZP,HI})$	0.004^{*}	0.004^{*}	0.002	0.002
$Ln(M_{PI,HI})$	0.001	0.001	0.0001	0.0001
$Ln(M_{AM,LI})$	0.003^{**}	0.003^{**}	0.0004	0.0005
$Ln(M_{CS,LI})$	0.007^{***}	0.007^{***}	-0.0002	-0.0002
$Ln(M_{ZP,LI})$	-0.0002	-0.0001	0.001	0.001
$Ln(M_{PI,LI})$	0.002	0.002	0.004^{***}	0.004^{***}
$Ln(M_{AM,HI}) * D_{HI}$	-0.003	-0.003	-0.005^{*}	-0.004^{*}
$Ln(M_{CS,HI}) * D_{HI}$	-0.009^{***}	-0.009^{***}	-0.002	-0.002
$Ln(M_{ZP,HI}) * D_{HI}$	-0.003	-0.003	-0.0003	-0.0002
$Ln(M_{PI,HI}) * D_{HI}$	0.003	0.003	-0.002	-0.002
$Ln(M_{AM,LI}) * D_{HI}$	-0.005^{*}	-0.005^{*}	-0.005	-0.004
$Ln(M_{CS,LI}) * D_{HI}$	-0.011^{***}	-0.011^{***}	-0.005^{**}	-0.005^{**}
$Ln(M_{ZP,LI}) * D_{HI}$	-0.003	-0.003	-0.002	-0.002
$Ln(M_{PI,LI}) * D_{HI}$	-0.006^{**}	-0.006^{**}	-0.006^{**}	-0.006^{**}
$Ln(Trade\ openness)$	0.050^{**}	0.049^{**}	0.049^{**}	0.049^{**}
$D_{HI} * Ln(Trade\ openness)$	-0.233^{***}	-0.234^{***}	-0.213^{***}	-0.214^{***}
$Ln(GDP)$	0.917^{***}		0.919^{***}	
$Ln(population)$		0.914^{***}		0.916^{***}
$Ln(GDP_{pc})$	2.672^{***}	3.591^{***}	2.785^{***}	3.708^{***}
$Ln(GDP_{pc})^2$	-0.186^{***}	-0.186^{***}	-0.192^{***}	-0.192^{***}
$Urban\ pop.(\%)$	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}
$Manufacturing\ (\%\ GDP)$	-0.0001	-0.0001	-0.0002	-0.0002
$Manufacturing\ (\%\ Exports)$	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
$Manufacturing\ (\%\ Imports)$	-0.0001	-0.0001	-0.0002	-0.0002
D_{HI}	1.093^{***}	1.099^{***}	0.963^{***}	0.968^{***}
Observations	2,808	2,808	2,800	2,800
R^2	0.660	0.659	0.653	0.652
Adjusted R^2	0.636	0.635	0.629	0.628
F Statistic (df = 26; 2624)	195.758^{***}	194.939^{***}	189.488^{***}	188.569^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Dependent variable: annual CO_2 in log. $Ln(M^{'}_{s,HI})$ and $Ln(M^{'}_{s,LI})$: annual M&A inflow in sector i from high-income and low-income countries, respectively. D_{HI}: dummy variable for the income level of the target country (1 if high-income country, 0 otherwise). The interaction between the M&A inflow variables and the dummy variable reflects the difference between the effect on low-income and high-income target countries. $Ln(GDP)$: log of GDP; $Ln(GDP)_{pc}$): log of GDP per capita; $Ln(GDP_{pc})^2$: log of GDP per capita squared; $Urban\ pop.(\%)$: urban population as percentage of total; $Manufacturing\ (\%\ GDP)$: Value added from manufacturing as percentage of GDP; $Manufacturing(\%Exports)$: Manufacturing exports as percentage of merchandise exports; $Manufacturing\ (\%\ Imports)$: Manufacturing imports as percentage of merchandise imports.

Table 6.2: Sector disaggregation (non-exhaustive)

Sector group	**Representative sectors**
A - Agriculture and Mining	Agriculture; Forestry; Fishing and Mining
C - Construction and Service	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; Fabricated metal products; Stone, clay and concrete products
Z - Zero Pollution Intensive	Apparel and other finished products made from fabrics and similar materials; Leather and leather products

Note: The disaggregation follows the one made by Swart and van Marrewijk (2011) who uses the ratio of kilograms of Carbon Monoxide Emission over the value of output, from the Industrial Pollution Projection System.

6.3 Sensitivity and Robustness checks

In this section, I present regressions tables made to test the sensitivity of my results and the robustness of the effect of M&A on CO_2 emissions. First, Table 6.6 shows three different models. Model 1 is the same as Model 1 in Table 6.1. Model 2 and 3 use a smaller sample size than Model 1. What separates Model 2 from Model 3 is that Model 3 uses an additional control variable labeled "Dirty electricity". This variable measures the percentage of electricity a country gets from coal and oil and it is meant to capture the composition effect of growth. This extra control variable was suggested by Swart and van Marrewijk (2011). The problem with using this variable is that it reduces the sample size. The purpose of Table 6.6 is to show that including dirty electricity does not affect the results. Model 3 does have different estimates than Model 1 but Model 2 and 3 are much alike. From this, we can deduce that it is not the extra control variable that changes the results but rather the fact that the sample size is lower.

Second, Table 6.7 tests the robustness of the effect of M&A on CO_2 emissions. Acquir-

Table 6.3: Fixed Effects Models for CO_2 emissions: M&A inflows in concurrent year - Pollution Intensive sector disaggregated

	Dependent variable: $Ln(CO_2)$			
	Deal Value		Target LTM Sales	
	(1)	(2)	(3)	(4)
$Ln(M_{AM,HI})$	0.002	0.002	0.002	0.002
$Ln(M_{CS,HI})$	0.003**	0.003**	−0.001	−0.001
$Ln(M_{ZP,HI})$	0.004	0.004	0.002	0.002
$Ln(M_{MP,HI})$	−0.0003	−0.0002	0.0002	0.0002
$Ln(M_{HP,HI})$	0.001	0.001	−0.0001	−0.0001
$Ln(M_{AM,LI})$	0.003*	0.003*	0.0005	0.0005
$Ln(M_{CS,LI})$	0.006***	0.007***	−0.0002	−0.0002
$Ln(M_{ZP,LI})$	−0.0002	−0.0001	0.001	0.001
$Ln(M_{MP,LI})$	0.003	0.002	0.004**	0.004**
$Ln(M_{HP,LI})$	0.002	0.002	0.002	0.002
$Ln(M_{AM,HI}) * D_{HI}$	−0.003	−0.003	−0.005*	−0.005*
$Ln(M_{CS,HI}) * D_{HI}$	−0.008***	−0.008***	−0.003	−0.002
$Ln(M_{ZP,HI}) * D_{HI}$	−0.003	−0.003	0.00000	0.00003
$Ln(M_{MP,HI}) * D_{HI}$	0.001	0.001	−0.001	−0.001
$Ln(M_{HP,HI}) * D_{HI}$	0.004	0.004	0.001	0.001
$Ln(M_{AM,LI}) * D_{HI}$	−0.005	−0.005	−0.004	−0.004
$Ln(M_{CS,LI}) * D_{HI}$	−0.011***	−0.011***	−0.005**	−0.005**
$Ln(M_{ZP,LI}) * D_{HI}$	−0.003	−0.003	−0.001	−0.001
$Ln(M_{MP,LI}) * D_{HI}$	−0.008***	−0.008***	−0.007***	−0.007***
$Ln(M_{HP,LI}) * D_{HI}$	0.001	0.001	0.003	0.003
$Ln(Trade\ openness)$	0.050**	0.050**	0.049**	0.049**
$D_{HI} * Ln(Trade\ openness)$	−0.238***	−0.239***	−0.210***	−0.211***
$Ln(GDP)$	0.925***		0.922***	
$Ln(population)$		0.922***		0.918***
$Ln(GDP_{pc})$	2.617***	3.544***	2.769***	3.693***
$Ln(GDP_{pc})^2$	−0.183***	−0.183***	−0.191***	−0.191***
$Urban\ pop.(\%)$	0.007***	0.007***	0.007***	0.007***
$Manufacturing\ (\%\ GDP)$	−0.0003	−0.0002	0.0002	0.0002
$Manufacturing\ (\%\ Exports)$	0.001***	0.001***	0.001***	0.001***
$Manufacturing\ (\%\ Imports)$	−0.00005	−0.0001	−0.0002	−0.0002
D_{HI}	1.119***	1.125***	0.951***	0.956***
Observations	2,808	2,808	2,800	2,800
R^2	0.661	0.661	0.654	0.653
Adjusted R^2	0.637	0.636	0.629	0.628
F Statistic (df = 26; 2624)	170.640***	169.912***	164.479***	163.676***

**p<0.1; **p<0.05; ***p<0.01*

Note: As in Table 6.1, except M&A inflow in the Pollution Intensive sector (PI) is now split into the Medium Pollution Intensive sector (MP) and the High Pollution Intensive sector (HP).

Table 6.4: Fixed Effects Models for CO_2 emissions: 1-year lagged M&A inflows

	Dependent variable: Ln(CO_2)			
	Deal Value		Target LTM Sales	
	(1)	(2)	(3)	(4)
$Ln(M_{AM,HI})_{t-1}$	0.001	0.002	0.001	0.001
$Ln(M_{CS,HI})_{t-1}$	0.003*	0.003*	−0.001	−0.001
$Ln(M_{ZP,HI})_{t-1}$	0.004	0.004	0.002	0.001
$Ln(M_{PI,HI})_{t-1}$	−0.001	−0.0005	−0.0004	−0.0004
$Ln(M_{AM,LI})_{t-1}$	0.003*	0.003*	−0.0002	−0.0002
$Ln(M_{CS,LI})_{t-1}$	0.005***	0.005***	0.00000	0.00000
$Ln(M_{ZP,LI})_{t-1}$	0.002	0.002	0.005	0.005
$Ln(M_{PI,LI})_{t-1}$	0.002	0.002	0.004**	0.004**
$Ln(M_{AM,HI})_{t-1} * D_{HI}$	−0.004	−0.004	−0.005*	−0.005*
$Ln(M_{CS,HI})_{t-1} * D_{HI}$	−0.010***	−0.010***	−0.002	−0.002
$Ln(M_{ZP,HI})_{t-1} * D_{HI}$	−0.003	−0.003	−0.001	−0.001
$Ln(M_{PI,HI})_{t-1} * D_{HI}$	0.0003	0.0004	−0.003	−0.003
$Ln(M_{AM,LI})_{t-1} * D_{HI}$	−0.006*	−0.006*	−0.002	−0.002
$Ln(M_{CS,LI})_{t-1} * D_{HI}$	−0.011***	−0.011***	−0.005**	−0.005**
$Ln(M_{ZP,LI})_{t-1} * D_{HI}$	−0.006	−0.006	−0.007	−0.007
$Ln(M_{PI,LI})_{t-1} * D_{HI}$	−0.006**	−0.006**	−0.006**	−0.006**
$Ln(Trade\ openness)$	0.060***	0.059***	0.055***	0.054***
$D_{HI} * Ln(Trade\ openness)$	−0.251***	−0.252***	−0.221***	−0.221***
$Ln(GDP)$	0.931***		0.922***	
$Ln(population)$		0.927***		0.918***
$Ln(GDP_{pc})$	2.746***	3.681***	2.889***	3.815***
$Ln(GDP_{pc})^2$	−0.189***	−0.189***	−0.196***	−0.196***
$Urban\ pop.(\%)$	0.005***	0.005***	0.006***	0.006***
$Manufacturing\ (\%\ GDP)$	0.0002	0.0003	0.001	0.001
$Manufacturing\ (\%\ Exports)$	0.001***	0.001***	0.001***	0.001***
$Manufacturing\ (\%\ Imports)$	−0.0003	−0.0003	−0.0003	−0.0004
D_{HI}	1.176***	1.181***	0.986***	0.990***
Observations	2,650	2,650	2,642	2,642
R^2	0.645	0.644	0.638	0.636
Adjusted R^2	0.618	0.617	0.611	0.610
F Statistic (df = 26; 2467)	172.160***	171.347***	166.448***	165.592***

$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: As in table 6.1, except now M&A inflow is not from the current year but from the previous year.

Table 6.5: Fixed Effects Models for CO_2 emissions: 1-year lagged M&A inflows - Pollution Intensive sector disaggregated

	Dependent variable: Ln(CO₂)			
	Deal Value		Target LTM Sales	
	(1)	(2)	(3)	(4)
$Ln(M_{AM,HI})_{t-1}$	0.001	0.001	0.001	0.001
$Ln(M_{CS,HI})_{t-1}$	0.003*	0.003*	−0.001	−0.001
$Ln(M_{ZP,HI})_{t-1}$	0.004	0.004	0.001	0.001
$Ln(M_{MP,HI})_{t-1}$	−0.001	−0.001	−0.0004	−0.0003
$Ln(M_{HP,HI})_{t-1}$	0.002	0.002	0.001	0.001
$Ln(M_{AM,LI})_{t-1}$	0.003*	0.003*	−0.0002	−0.0002
$Ln(M_{CS,LI})_{t-1}$	0.005***	0.005***	−0.0001	−0.0001
$Ln(M_{ZP,LI})_{t-1}$	0.002	0.002	0.004	0.005
$Ln(M_{MP,LI})_{t-1}$	0.002	0.002	0.004*	0.004*
$Ln(M_{HP,LI})_{t-1}$	0.001	0.001	0.001	0.001
$Ln(M_{AM,HI})_{t-1} * D_{HI}$	−0.004	−0.004	−0.005*	−0.005*
$Ln(M_{CS,HI})_{t-1} * D_{HI}$	−0.010***	−0.010***	−0.002	−0.002
$Ln(M_{ZP,HI})_{t-1} * D_{HI}$	−0.002	−0.002	−0.0004	−0.0004
$Ln(M_{MP,HI})_{t-1} * D_{HI}$	0.00001	−0.00003	−0.001	−0.002
$Ln(M_{HP,HI})_{t-1} * D_{HI}$	0.0003	0.0004	−0.001	−0.001
$Ln(M_{AM,LI})_{t-1} * D_{HI}$	−0.006*	−0.005*	−0.002	−0.002
$Ln(M_{CS,LI})_{t-1} * D_{HI}$	−0.011***	−0.011***	−0.005**	−0.005**
$Ln(M_{ZP,LI})_{t-1} * D_{HI}$	−0.006	−0.006	−0.006	−0.006
$Ln(M_{MP,LI})_{t-1} * D_{HI}$	−0.006**	−0.006**	−0.007**	−0.007**
$Ln(M_{HP,LI})_{t-1} * D_{HI}$	−0.002	−0.002	−0.001	−0.001
$Ln(Trade\ openness)$	0.060***	0.060***	0.055***	0.054***
$D_{HI} * Ln(Trade\ openness)$	−0.251***	−0.252***	−0.217***	−0.218***
$Ln(GDP)$	0.934***		0.922***	
$Ln(population)$		0.930***		0.918***
$Ln(GDP_{pc})$	2.726***	3.665***	2.887***	3.813***
$Ln(GDP_{pc})^2$	−0.188***	−0.188***	−0.196***	−0.196***
$Urban\ pop.(\%)$	0.005***	0.005***	0.006***	0.006***
$Manufacturing\ (\%\ GDP)$	0.0001	0.0002	0.001	0.001
$Manufacturing\ (\%\ Exports)$	0.001***	0.001***	0.001***	0.001***
$Manufacturing\ (\%\ Imports)$	−0.0003	−0.0003	−0.0003	−0.0004
D_{HI}	1.172***	1.177***	0.964***	0.968***
Observations	2,650	2,650	2,642	2,642
R^2	0.645	0.644	0.638	0.636
Adjusted R^2	0.618	0.617	0.610	0.609
F Statistic (df = 30; 2463)	149.216***	148.499***	143.990***	143.235***

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: As in table 6.3, except now M&A inflow is not from the current year but from the previous year.

ing another company is a complex process. It takes time to successfully synthesize and integrate a newly acquired firm. According to Investopedia this process often takes between one and three years ("How Long Does It Take to Execute an M&A Deal?", n.d.). Therefore, Table 6.7 considers the four different regression models where M&A is lagged by 0, 1, 2, and 3 years, respectively. The results imply that the effects of M&A on CO_2 emissions seem to be robust over different lags. Still, we do see that the estimated coefficients are less significant at lag 3 and the models perform worse the more we increase the lag.

6.4 Discussion

Contrary to my initial expectations, the results did not indicate that M&As from a high-income country (acquiring country) reduce CO_2 emissions. Instead, they indicate that it is the income level of the target country that matters for the impact of M&A. M&A going to a high-income country reduces emissions while M&A going to a low-income country increases emissions. It suggests that acquiring firms take advantage of the less strict environmental regulations in low-income countries while they need to adjust to the stricter environmental regulations in high-income countries.
Surprisingly, the sector where I observed the most significant effects was Construction & Service. This suggests that there might be a spill-over effect at play. For instance, it could be the case that target companies from high-income countries within Construction & Service use the extra capital to choose cleaner suppliers following an acquisition while those from low-income countries are not given the lower incentive provided by laxer regulation. Another surprising finding is that I find significant effects from M&A in the Medium Pollution Intensive sector but not from the High Pollution Intensive sector. It is important to note from the summary statistics that the data availability is much better for the Medium Pollution Intensive sector than for the High Pollution Intensive sector.

Table 6.6: Fixed Effects Models for CO_2 emissions: Sensitivity check

	Dependent variable: Ln(CO_2)		
	Deal Value		
	(1)	(2)	(3)
$Ln(M_{AM,HI})$	0.002	0.004***	0.004***
$Ln(M_{CS,HI})$	0.003***	0.0001	0.002
$Ln(M_{ZP,HI})$	0.004*	0.003	0.002
$Ln(M_{PI,HI})$	0.001	−0.0003	−0.0001
$Ln(M_{AM,LI})$	0.003**	0.003*	0.003*
$Ln(M_{CS,LI})$	0.007***	0.004***	0.003***
$Ln(M_{ZP,LI})$	-0.0002	0.003	0.002
$Ln(M_{PI,LI})$	0.002	0.001	0.001
$Ln(M_{AM,HI}) * D_{HI}$	-0.003	−0.003	−0.004*
$Ln(M_{CS,HI}) * D_{HI}$	-0.009***	−0.0001	−0.001
$Ln(M_{ZP,HI}) * D_{HI}$	-0.003	−0.003	−0.002
$Ln(M_{PI,HI}) * D_{HI}$	0.003	−0.002	−0.002
$Ln(M_{AM,LI}) * D_{HI}$	-0.005*	−0.007**	−0.004
$Ln(M_{CS,LI}) * D_{HI}$	-0.011***	−0.008***	−0.007***
$Ln(M_{ZP,LI}) * D_{HI}$	-0.003	−0.004	−0.002
$Ln(M_{PI,LI}) * D_{HI}$	-0.006**	−0.005*	−0.002
$Ln(Trade\ openness)$	0.050**	0.107***	0.104***
$D_{HI} * Ln(Trade\ openness)$	-0.233***	−0.280***	−0.257***
$Ln(GDP)$	0.917***	0.976***	1.057***
$Ln(GDP_{pc})$	2.672***	1.608***	1.456***
$Ln(GDP_{pc})^2$	-0.186***	−0.124***	−0.118***
$Urban\ pop.(\%)$	0.007***	0.005***	0.004**
$Manufacturing\ (\%\ GDP)$	-0.0001	−0.0004	0.001
$Manufacturing\ (\%\ Exports)$	0.001***	0.001***	0.001***
$Manufacturing\ (\%\ Imports)$	-0.0001	0.001***	0.001***
D_{HI}	1.093***	1.241***	1.163***
$Dirty\ electricity$			0.005***
Observations	2,808	1,766	1,766
R^2	0.660	0.661	0.703
Adjusted R^2	0.636	0.630	0.675
F Statistic	195.785***	121.395***	141.535***

**p<0.1; **p<0.05; ***p<0.01*

Note: This table compares three models. Model 1 is the first model from Table 6.1 with 2,808 observations. Model 2 is specified as model 1 but with fewer observations. Model 3 adds Dirty electricity as a control variable and uses the same sample as Model 2. Dirty electricity=Electricity production from coal and oil sources as percentage of total. The variables have the same interpretation as in table 6.1.

Table 6.7: Fixed Effects Models for CO_2 emissions: Robustness check for lags 0 through 3

	Dependent variable: $Ln(CO_2)$			
	Concurrent i=0	1-year lag i=1	2-year lag i=2	3-year lag i=3
$Ln(M_{AM,HI})_{t-i}$	0.002	0.001	0.001	0.001
$Ln(M_{CS,HI})_{t-i}$	0.003**	0.003*	0.003**	0.002
$Ln(M_{ZP,HI})_{t-i}$	0.004*	0.004	0.004	0.002
$Ln(M_{PI,HI})_{t-i}$	0.001	−0.001	−0.0001	−0.0001
$Ln(M_{AM,LI})_{t-i}$	0.003**	0.003*	0.004**	0.003*
$Ln(M_{CS,LI})_{t-i}$	0.007***	0.005***	0.004***	0.003**
$Ln(M_{ZP,LI})_{t-i}$	−0.0002	0.002	0.002	−0.003
$Ln(M_{PI,LI})_{t-i}$	0.002	0.002	0.002	0.002
$Ln(M_{AM,HI})_{t-i} * D_{HI}$	−0.003	−0.004	−0.005*	−0.004
$Ln(M_{CS,HI})_{t-i} * D_{HI}$	−0.009***	−0.010***	−0.007***	−0.003
$Ln(M_{ZP,HI})_{t-i} * D_{HI}$	−0.003	−0.003	−0.005	−0.005
$Ln(M_{PI,HI})_{t-i} * D_{HI}$	0.003	0.0003	0.0001	−0.0004
$Ln(M_{AM,LI})_{t-i} * D_{HI}$	−0.005*	−0.006*	−0.005*	−0.005*
$Ln(M_{CS,LI})_{t-i} * D_{HI}$	−0.011***	−0.011***	−0.011***	−0.012***
$Ln(M_{ZP,LI})_{t-i} * D_{HI}$	−0.003	−0.006	−0.007	0.0002
$Ln(M_{PI,LI})_{t-i} * D_{HI}$	−0.006**	−0.006**	−0.009***	−0.008***
$Ln(Trade\ openness)$	0.050**	0.060***	0.075***	0.081***
$D_{HI} * Ln(Trade\ openness)$	−0.233***	−0.251***	−0.247***	−0.233***
$Ln(GDP)$	0.917***	0.931***	0.940***	0.945***
$Ln(GDP_{pc})$	2.672***	2.746***	2.787***	3.004***
$Ln(GDP_{pc})^2$	−0.186***	−0.189***	−0.191***	−0.203***
$Urban\ pop.(\%)$	0.007***	0.005***	0.004***	0.003*
$Manufacturing\ (\%\ GDP)$	−0.0001	0.0002	0.0004	0.0005
$Manufacturing\ (\%\ Exports)$	0.001***	0.001***	0.001**	0.001**
$Manufacturing\ (\%\ Imports)$	−0.0001	−0.0003	−0.0001	−0.0001
D_{HI}	1.093***	1.176***	1.133***	1.063***
Observations	2,808	2,650	2,493	2,336
R^2	0.660	0.645	0.628	0.609
Adjusted R^2	0.636	0.618	0.599	0.576
F Statistic	195.758***	172.160***	150.229***	129.101***

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: This table compares four models. Model 1 uses M&A inflow from the current year while Models 2, 3, and 4 use 1-year lagged, 2-year lagged, and 3-year lagged M&A inflow, respectively. The variables have the same interpretation as in Table 6.1.

Finally, as stated earlier the sector disaggregation of this paper is based on the one made by Swart and van Marrewijk (2011). Given that this was done more than ten years ago, it is natural to question whether it is still appropriate. For instance, the decision to group construction and service companies is a little odd given that the nature of construction and service companies is very different. One would expect that a construction company pollutes more than for instance a financial service company. For future research it would therefore be relevant to consider whether a new sector disaggregation should be applied.

CHAPTER 7: CONCLUSION

In conclusion, this paper has investigated the relationship between cross-border M&A and pollution. It has done so by considering the effect of annual M&A inflows within different sectors on annual CO_2 emissions. I test two hypotheses. First, M&As from a high-income country (acquiring country) reduce CO_2 emissions. Second, only M&As in polluting sectors affect CO_2 emissions. The evidence of a sector-specific impact is mixed. I get different results when I use deal value than when I use target LTM sales. However, I find the most significant effects within the Pollution Intensive sector and Construction & Services. The latter is surprising and suggests a spill-over effect. It also calls for an updated sector disaggregation. When it comes to the asymmetry aspect, the evidence is very clear though. I do not find evidence that supports the hypothesis that M&A from high-income countries reduces CO_2 emissions but it is quite clear from the results that M&A flowing to a high-income country has a less positive and sometimes even negative effect on CO_2 emissions. This leads to the main finding of this paper. It is not where M&A is coming from that matters for its effect on pollution, it is where it is going.

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APPENDIX A: THE DATA COLLECTION PROCESS

- Step 1 - Extracting M&A data

  Using the Dealscreener tool in Refinitiv Workspace, I collected data on M&A transactions in the period 2000-2020. The exact filters used were: - Deal Status: Completed - Cross Border Deal Flag: True - Period (Date Effective): January 1, 2000 - December 31, 2020.

  The columns that I asked to have displayed for each transaction were: SDC Deal No, Rank Value inc. Net Debt of Target, Target Full Name, Target Nation, Acquiror Full Name, Acquiror Nation, Date Effective, Deal Value, Target Net Sales Last 12 Months, Target Primary SIC, Target Primary SIC Code

- Step 2 - Extracting country-level data from World Bank

  Using the WDI package in R, I extract data on CO_2 emissions, GDP (constant 2015 USD), GDP per capita (constant 2015 USD), manufactures export (% of merchandise exports), manufactures import (% of merchandise imports), population, trade (% of GDP), urban population (% of population), manufacturing - value added (% of GDP), and GNI per capita (current USD) for the period 1998-2020.

  The exact ID's I use are: EN.ATM.CO2E.KT, NY.GNP.PCAP.CD, NY.GDP.MKTP.KD, SP.POP.TOTL, NY.GDP.PCAP.KD, TX.VAL.MANF.ZS.UN, TM.VAL.MANF.ZS.UN, NE.TRD.GNFS.ZS, SP.URB.TOTL.IN.ZS, NV.IND.MANF.ZS.

- Step 3 - Country classification

  Following the historical income classification method from the World Bank I classified the target nation as either "High-income" or "Low-income". This was based on the country's two-year lagged GNI per capita level. Having done this I was able to classify the acquirer nation in each transaction as well.

- Step 4 - Aligning country names

  World Bank and Refinitiv use slightly different names for the same countries (e.g. Czech Republic vs. Czechia and TÃŒrkiye vs. Turkiye). Therefore, I had to replace the country names in my transaction data with the names used by the World Bank. The two datasets also included countries/areas which the other set did not. Thus, I had to drop countries/areas such as Curacao, Sudan, Taiwan, Cook Islands etc.

- Step 5 - Classifying transactions according to industry group

  Using the 4-digit SIC code for the target in each transaction I was able to make an industry classification for each transaction by comparing the 4-digit SIC code with the classification described by Swart and van Marrewijk (2011). 732 transactions belonged to an SIC code which was not grouped by Swart and van Marrewijk. These transactions were therefore dropped.

- Step 6 - Aggregating M&A activity on a country-level

  To get country-level variables that reflect the level of M&A inflow going to a specific country in a specific year, I grouped transactions by sector and acquirer nation income level and summed the deal value of transactions going to each country in each year. For instance, summing the deal value of transactions in Agriculture & Mining in 2020 coming from a high-income country and going to the United States amounted to 2198.719 USDm. I did the same using target LTM sales instead of deal value as a measure of M&A activity.

- Step 7 - Preparing variables for regression and removing incomplete observations

  I made certain adjustments to the variables in order to get them ready for regression. First, I multiplied CO_2 emissions by 1000 and took logs. Second, I took logs of GDP, GDP per capita, trade, and population. Third, I added 100,000 USD and took logs of all M&A inflow variables. Fourth, I created lagged M&A inflow variables that reflected a country's M&A inflow level in the prior years.

- Step 8 - Removing incomplete observations

  As a final step, I removed all incomplete observations. This left me with 2,808 observations covering the period 2000-2020 and 158 countries.

APPENDIX B: ADDITIONAL SUMMARY STATISTICS

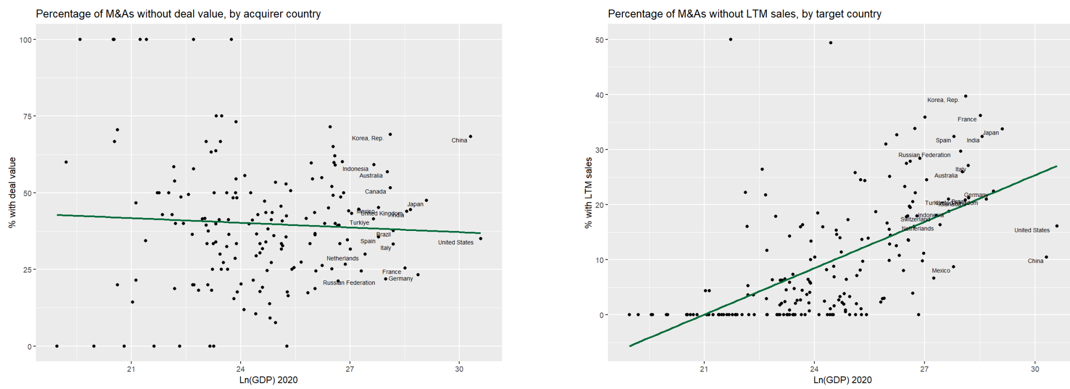

Figure B.1: Transactions with deal value by target country and acquirer country, respectively

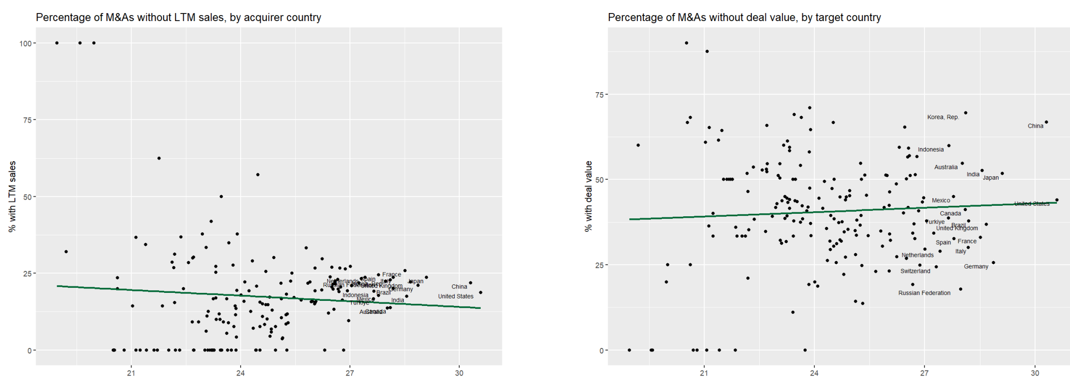

Figure B.2: Transactions with LTM sales value by target country and acquirer country, respectively