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Belgium and the Kyoto Protocol: A decomposition of air emissions and sectoral development patterns

by

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Abstract

Based on a two-step decomposition analysis using the logarithmic mean divisia index (LMDI), this paper analyses the change of greenhouse gas (GHG) emissions in Belgium over the period from 2008 to 2018. This ten-year period is furthermore aggregated into two distinct time periods to evaluate emission drivers during the two commitment periods of the Kyoto Protocol. The changes in GHG emissions are decomposed into the contribution of the determinants of economic activity, energy intensity, emission intensity, structural change, and population. Additionally, the economy of Belgium is represented in form of six economic sectors, whose contribution to emission changes is also evaluated. The obtained results indicate that Belgium significantly lowered its emission reduction efforts during the second commitment period in comparison to the first commitment period. Moreover, the conducted analysis suggests that the general impact of economic sectors on emissions has fallen over time, while the same cannot be said of the determinants. Overall, energy intensity, emission intensity and structural change appear to have the strongest impact on emission changes in Belgium. Based on the obtained results, environmental protection policies are advised to address energy-related determinants as the most effective levers in reducing GHG emissions.

Keywords: air pollutants, logarithmic mean divisia index, decomposition analysis

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1 Introduction

The emission of *greenhouse gases* (GHG) is the main contributor to climate change worldwide. These greenhouse gases mostly consist of water vapor (H_2O), carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) and are released to the Earth's atmosphere (Kweku et al., 2017). This collection of atmospheric gases serves as effective global insulators and are called greenhouse gases as they capture and store heat similar to glass walls of a greenhouse (Kweku et al., 2017). Likewise, the resulting effect of this atmospheric gas insulation on global temperature is called the *greenhouse effect*. Despite the regular negative connotation of the greenhouse effect, the effect itself is not necessarily harmful to Earth's environment. In fact, the greenhouse effect is the foremost factor in keeping the Earth habitable by keeping global temperature within a comfortable range. It is a natural process that is millions of years old and plays a crucial role in regulating the overall temperature of Earth (Kweku et al., 2017). It is the concentration of greenhouse gases in the atmosphere, however, that plays a crucial role for climate change and global warming. Human activities such as the extraction and consumption of fossil fuels, the use of chemicals for industrial processes, or deforestation and agriculture strongly increase the concentration of GHG within the atmosphere, thus making them harmful (El-Fadul & Massoud, 2001). Atmospheric CO_2 concentration, for instance, has increased to 48 percent above its pre-industrial level (European Commission, 2021). Furthermore, according to the European Commission, human-induced global warming is currently rising at a rate of 0.2 percent per decade (European Commission, 2020). While not being of much relevance around the time of the Industrial Revolution, the growing concern for greenhouse gases and their effects on global temperature sparked international policy efforts to maintain atmospheric gas levels at reasonable levels. These policy efforts culminated in the 1992 *United Nations Framework Convention on Climate Change* (UNFCCC) and subsequently in the negotiation of the famous *Kyoto Protocol* in 1997.

1.1 Belgium and the Kyoto Protocol

The Kyoto Protocol is the first legally binding international agreement on climate protection (Böhringer, 2003). Within this protocol, a single European Union reduction target for greenhouse gas emissions of minus 8 percent compared to the base year 1990 was negotiated for the first commitment period from 2008 to 2012. Moreover, a *Burden Sharing Agreement* between the then 15 member states of the European Union allocated this reduction target between countries. The Kyoto Protocol was signed and ratified by Belgium in 1998 and 2002, respectively (Van Hecke & Zgajewski, 2008). Under the burden sharing agreement, Belgium was required to cut its emissions by 7.5 percent compared to 1990 levels during the first commitment period from 2008 to 2012 (European Commission, 2019). According to Belgium's *2021 National Inventory Report* of greenhouse gases, Belgium complied to its commitments during the first commitment period and even reduced emissions by 13.9 percent during that time span (Belgium, 2021). Moreover, *Belgium's Seventh National Communication on Climate Change* (National Climate Commission, 2017) argues that by 2015, Belgium already decreased GHG emissions by 20 percent compared to 1990 levels while still growing in terms of gross domestic product (GDP). As such, Belgium strongly contributed to the overall cut of 11.7 percent of GHG emissions that took place the European Union (EU) between 2008 to 2012 (European Commission, 2020). As not all European countries were equally successful in their efforts of cutting GHG emissions and still maintaining economic growth, Belgium poses a highly interesting example for analysing what factors drove the apparent decoupling of emissions from economic growth and where in the economy emission reductions were most significant. Analysing the underlying reasons of Belgian emission changes becomes even more pressing when recalling the role Belgium plays for the European Union as a whole.

According to Article 13 of the Treaty on the European Union, the EU institutional framework is comprised of seven institutions (European Union, 2012). These institutions include the European Parliament, the European Council, the Council, the European Commission, the Court of Justice of the European Union, the European Central Bank, and the Court of Auditors (European Union, 2012: p. 22). Out of these seven institutions, three are operating from Belgium[1]. As such, Belgium is the location with the most EU institutions out of all members of the European Union. Consequently, Belgium possesses a strong signalling value for the EU as a whole and is one of only a few countries within the European Union where emission-related reforms and policies are being implemented from. Moreover, with 122.628 kilo tonnes of CO_2 equivalent in GHG emissions, Belgium was among the Top 10 of countries in the European Union with the highest emission footprint in 2018 (EEA, 2020). However, despite this seemingly pressing relevance of Belgium for emission research, the literature body concerning the driving forces of Belgian emission changes remains scarce. In the next chapter, I will elaborate how the aim and scope of this thesis try to address this scarcity.

[1] The institutions located in Belgium include the European Council, the European Commission, as well as the Council.

1.2 Research Aim and Scope

Examining the driving factors of emission changes is crucial to find the economically most efficient ways to reduce GHG emissions based on data on countries' GHG emissions throughout sectors and time. Understanding the underlying forces of a reduction or increase in greenhouse gas emissions becomes particularly important when trying to affect emission changes from a policy point of view, as policies will be most effective when the main reason for the emission change is addressed. The objective of this paper is thus to analyse the underlying drivers of changes in greenhouse gas emissions between 2008 and 2018 in Belgium. In doing so, I differentiate between a *first commitment period* (2008-2012) as established by the Kyoto Protocol and a *second commitment period* from 2013-2018. The first commitment period directly relates to the formally established commitment period in the 1997 adoption of the Kyoto Protocol and entered into force together with the Kyoto Protocol on the 16th of February 2005 (United Nations, 2021). The second official commitment period, however, was adopted in the *Doha Amendment* of the Kyoto Protocol in 2012 and ranges from 2013 to 2020. In this amendment, the Annex B countries[2] agreed to extend the Kyoto Protocol to 2020 and to reduce their emissions by 18 percent until 2020 compared to 1990 base levels (German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2021). Notably, the second commitment period analysed in this paper ranges from 2013 to 2018 only. Unfortunately, the data needed to examine the driving forces of emission changes for the years 2019 and 2020 is not yet provided in the data sources used for this paper. However, the slightly shortened commitment period from 2013 to 2018 represents 75 percent of the official second commitment period as established by the Doha amendment and as such is considered to provide a good indication for emission trends in Belgium during the second commitment period of the Kyoto Protocol.

Using the Logarithmic Mean Divisia Index (LMDI) decomposition method as presented by Ang and Liu (2001), I take a more detailed look at the underlying dynamics of Belgium's emission reduction and examine what economic sectors and determinants drove this reduction. In doing so, I differentiate between five determinants that can change GHG emissions on a sectoral level. Those determinants include an economic activity effect (D_{act}), a structural change effect (D_{str}), an energy intensity effect (D_{int}), an emission intensity effect (D_{eint}), as well as a population effect (D_{pop}). Furthermore, the decomposition analysis within this paper represents

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[2] The Annex B countries include the following countries: all EU-15 states, United States, Canada, Hungary, Japan, Poland, Croatia, New Zealand, Russia, Ukraine, Norway, Australia, and Iceland.

the economy of Belgium in form of six economic sectors. The sectors within the analysis include an *Agriculture* sector, an *Industry* sector, an *Energy* sector, a *Services* sector, a *Transport* sector, and a *Residential* sector. Together, these sectors represent the full economic activity of the Belgian economy. Within the next chapter, a brief introduction to the different determinants and economic sectors is given.

1.2.1 Decomposition Determinants and Economic Sectors

In essence, the five determinants within this paper describe different economic variables that explain an observed change of GHG emissions in Belgium. The first of the determinants, the *economic activity effect*, is capturing to what degree changes in GHG emissions occur due to changes in the gross value added (GVA) per capita. GVA in general is indicating the value of the goods and services produced within a given economy or sector. Historically, a growing economy typically experiences growing emissions due to increased economic productivity, as emissions were found to be positively correlated with economic growth (Acheampong, 2018). As such, the first effect examines what impact GVA per capita changes in Belgium had on its emission development. The *structural change effect*, on the other hand, is capturing to what degree changes in an economy's activity structure impact greenhouse gas emission changes. As an example, it is expected to observe declining emissions for countries that switch from energy intensive activities in primary and secondary sectors, such as mining and industry, to activities in tertiary service sectors (Luukkanen et al., 2015). The third effect, the *energy intensity effect*, is indicating how changes in energy intensity have affected GHG emissions. Energy intensity, often used as a proxy for energy efficiency (Proskuryakova & Kovalev, 2015), is essentially capturing how much energy needs to be consumed to produce one unit of output. Changes in energy intensity are typically the result of technological improvements in existing production technologies or from switching to different production technologies (Cansino et al., 2015). As such, this effect partially changes due to technological progress. The *emission intensity effect* is capturing to what degree GHG emissions change due to changes in emission intensity. Emission intensity itself is indicating the ratio of consumed energy to one unit of emission output. Changes to emission intensity are typically the result of switching to cleaner energy sources with less embodied emission content, for instance by switching from brown coal to natural gas as an energy source (Wang et al., 2017). The last effect, the *population effect*, is indicating to what degree changes in the population of Belgium impacted GHG emissions. If every individual is considered an emission source, then a growing number of individuals will most likely also lead to a growing number of emissions.

Within the LMDI decomposition applied in this paper, the change in GHG emissions from one year to another can be fully explained by the five determinants discussed above without any unexplained residuals. Aside from analysing the impact of each of these five determinants, the decomposition results will furthermore differentiate between different economic sectors. The Belgian economy will be depicted in form of six economic sectors that represent the full economic activity. These sectors include an *Agriculture* sector, an *Industry* sector, an *Energy* sector, a *Services* sector, a *Transport* sector, as well as a *Residential* sector. Similar to the five determinants discussed above, the LMDI decomposition analysis performed within this paper will allow to assess the impact of each of those six sectors on GHG emissions to evaluate which parts of the economy were of most relevance for a change in emissions. Hence, it will be possible to not only assess the impact of the determinants on emission changes, but also to evaluate which parts of the economy contributed most to changes in GHG emissions. The purpose of this sectoral differentiation is ultimately linked to the aim of providing an actionable knowledge base for policymakers to draw from. Isolating the contributions of each sector and determinant to emission changes enables policymakers to tackle the drivers of emission changes at the very root by directly addressing the respective parts of the economy. Within the next chapter, a brief outline on how this thesis was designed to reach its research aims is given.

1.3 Outline of the Thesis

When drafting the overall design of this thesis, one of the most important aspects was to explain the observed change in emissions as accurately as possible. This means to not only evaluate the changes from the start year to the end year of a given period, but rather to also analyse the annual emission changes for all years entailed in that period. Additionally, the five determinants discussed before may be unequally powerful in their impact on emission changes throughout time and across economic sectors. For this reason, I am first examining emission changes in Belgium per sector on a time series basis between 2008 and 2018, where I decompose emission changes from each year to the next one. Afterwards, I aggregate the results of the time series analysis into two distinct time periods, with each of these periods representing a commitment period relating to the ones as established in the Kyoto Protocol. This enables the reader to not only understand the driving forces of emission changes on a yearly basis, but to rather grasp the full effect of these forces in the light of the first international agreement on climate protection. Given Belgium’s apparent success in cutting emissions during the commitment periods of the Kyoto Protocol, I hope that my analysis provides valuable insights that allow for a deeper understanding of what drove this reduction. Moreover, the results of my decomposition analysis of GHG emission changes in Belgium might serve as guidance towards future policy implementations.

Greenhouse gas emissions, although being released locally, have increasingly global consequences. As such, trying to devise the economically most efficient policies poses an increasingly difficult challenge for national governments and international institutions such as the European Union alike. Identifying what factors drive an emission reduction or increase is thus of great value, as it enables policymakers to devise policies that directly target the main emission determinants on a sectoral level. For this task to be prepared, policymakers need information not only of the determinant contribution on an economy-wide level, but rather on the sectoral contribution to GHG emission changes as well. Hence, based on Belgium’s GHG emission changes between 2008 and 2018, I state the following two research questions for my analysis:

1. *How do the determinants and economic sectors affect greenhouse gas emissions in Belgium between 2008 and 2018?*

2. *What are the driving forces of greenhouse gas emission changes within and across the two commitment periods of the Kyoto Protocol in Belgium?*

The first research question is intended to evaluate how the determinants, as well es each economic sector, contributed to Belgian emission changes between 2008 and 2018. With doing so, I hope to produce results that illustrate potential developments such as if Belgium has indeed become more efficient in their use of energy (indicated by the energy intensity effect) and whether or not increased per capita GVA results in increased emissions (indicated by the economic activity effect). The second research question is intended to investigate the differences in the underlying factors that facilitate the changes in GHG emissions and to see how they change based on the time aggregation level. The main intention behind this question is to see how the previous results regarding the driving forces of emission changes obtained for the first research question behave when looking at the two commitment periods separately. As there is a potentially large difference between the results based on the time aggregation level, I hope to produce outcomes that showcase the determinants of emission changes on multiple scales. After this introduction, this thesis will continue with a comprehensive literature and theory review of different relevant studies, books and articles on the subjects of either decomposition analysis or emission research in general. Throughout the theory section, I will lay focus on isolating those parts of previous literature that are relevant for the analysis conducted within this thesis. Furthermore, I will take time to explain why my research was designed as it is now and how the previous research body contributed to this design. Chapter 3 will explain the different sources and compilation techniques that were used to compile the database used for the decomposition analysis within this paper. After illustrating the data that is being used, chapter 4 will then break down the methodology and mathematical formulae used to answer the research questions. Afterwards, I will present the results of the conducted analysis and a discussion part will deliberate about the outcomes and policy implications of the results obtained within this thesis. Ultimately, a conclusion is summarizing the findings of this paper.

2 Theory

In general, decomposition analysis is concerned with deriving determinants that explain the change of a given indicator, such as for example GHG emissions. When looking at the literature body addressing the determinants of greenhouse gas emissions, a strong surge can be observed over the past decades. With emission monitoring and climate change becoming more present topics in policy and academia alike, assessing the drivers of emission changes has attracted great research interest across multiple study fields. Throughout those study fields, various approaches on how to assess the determinants that underlie emission changes have emerged. Two of the most prominent examples of evaluating changes in indicators such as greenhouse gas emissions are the *structural decomposition analysis* (SDA) and the *index decomposition analysis* (IDA). These two types of decomposition analyses have been particularly popular within energy research and environmental studies. Ang and Zhang (2000) have discussed 109 IDA articles in these fields, while Hoekstra and van den Bergh (2002) summarized 29 SDA publications belonging to either environmental or energy research. Although both methods decompose the change of a chosen indicator, they have developed rather independently (Hoekstra & van den Bergh, 2003) and are characterized by some peculiarities that have a significant impact on the decomposition results. The following chapters will first illustrate the differences between the two decomposition approaches and then gradually go into more detail with regards to different theories and methodologies that had an impact on the present research design. Ultimately, it will be explained what is yet missing in emission research and decomposition analyses and how this thesis is contributing to filling the existing literature gap.

2.1 Structural Decomposition Analysis

In general, literature on structural decomposition analysis (SDA) has focused on distinguishing a large number of specific determinant effects (Hoekstra & van den Bergh, 2003) for a given indicator. Typically, historical data from two years is analysed to reveal to what degree each determinant has contributed to the observed indicator change. An important aspect to note is that information and data needed for SDA is taken from an input-output framework[3]. These input-output frameworks describe the sale and purchase relationships between producers and consumers within an economy (OECD, 2021). The usage of such input-output data has important implications for the subsequent decomposition analysis. Originally, using input-output based analyses for studying environmental effects was introduced in the late 1960s (see Isard et al., 1968; Daly, 1968; Leontief & Ford, 1972). With the introduction of the environmentally extended input output framework by Isard et al. (1968) and Leontief (1970), scholars were able to analyse economy-wide energy consumption and emissions. Subsequent structural decomposition analyses adopted this newly extended input output framework and initially focused on changes in energy-related indicators (Chen & Rose, 1990; Rose & Chen, 1991). However, as the growing importance of climate change has become apparent, scholars started to apply SDA to environmental indicators such as greenhouse gas emissions as well.

Casler and Rose (1998), for instance, use a slightly modified version of the SDA framework illustrated by Rose and Chen (1991) to decompose the change in CO_2 emissions between 1972 and 1982 in the United States. In doing so, they differentiate between ten effects that change CO_2 emissions. These effects are furthermore aggregated into three broader effect categories, namely final demand effects, changes within aggregates effects, as well as KLEM[4] effects (Casler & Rose, 1998). The study concluded that although economic growth strongly increased carbon emissions in the U.S. during the observed time period, this increase was more than offset by the negative structural effects exerted by fuel substitutions and KLEM substitutions (Casler & Rose, 1998). Later, multiple other studies have further investigated national emission changes using SDA and produced interesting insights (see for example Wier, 1998; De Haan, 2001; Roca & Serrano, 2007; Lim et al., 2009). In a more recent study, Wang et al. (2017) used SDA to decompose global CO_2 emission intensity changes. In doing so, they apply one global SDA model and one country level SDA model to quantify domestic and trade related effects. They conclude that the main contributor to decreases in global emission intensity was a change in emission efficiency, while international trade appears to have slightly hampered improvements in global emission intensity (Wang et al., 2017).

Such previous studies showed that SDA is a valuable and widely anticipated method to decompose emission changes. One advantage is that due to the comprehensive structural data of input-output tables, SDA is capable of more detailed decompositions of the economic

[3] SDA is sometimes also referred to as “input-output decomposition analysis” or “input-output structural analysis” (Hoekstra & van den Bergh, 2003) due to its connection to the input-output framework.

[4] KLEM is an acronym summarizing capital (K), labour (L), energy (E) and materials (M).

structure than IDA. Moreover, input-output tables allow for a distinction between technological effects and final demand effects. This, amongst other aspects, enables SDA to include indirect effects that are not part of the IDA analysis (Hoekstra & van den Bergh, 2003). These indirect effects can be characterized as spill-over effects of demand that are captured by the Leontief-Inverse of input-output models (Miller & Blair, 1985). The Leontief Inverse itself can be thought of as an indicator of the technological effect of changes in the intermediate output structure (Hoekstra & van den Bergh, 2003). However, even though SDA allows for capturing indirect effects and enables a more detailed analysis of the economic structure, it has been found to be inferior to IDA for the research purpose within this thesis. The first problem with using SDA for this thesis is that the data needed from input-output tables is not constructed annually for all sectors that are part of this research. Moreover, the six economic sectors analysed in this paper are aggregates of a larger set of economic activities that depict Belgium's economy. As already pointed out by Su and Ang (2012), there are several issues with sector aggregation, spatial aggregation, and time aggregation using SDA. Particularly the issues regarding sector and time aggregation are relevant for the analysis conducted in this paper, as I aggregate a multitude of economic activities into only six sectors and furthermore aggregate a ten-year timespan into two distinct periods of time. Consequently, there are two potential aggregation issues within my analysis, which may lead to additional interaction issues when relying on input-output data and SDA (Su & Ang, 2012). Secondly, SDA in general limits itself to evaluating the absolute change of a given indicator, with only a few exceptions such as in Dietzenbacher et al. (2000), who decomposed labour productivity growth into partial effects of six determinants. Even though examining the absolute change of GHG emissions would be feasible as well, the approach chosen for this thesis will decompose emissions into relative values in form of determinants. This provides a more intuitive understanding of the results and allows for a better contextualization of the analysis in light of the commitment periods of the Kyoto Protocol. In the next subchapter, the literature on index decomposition analysis will be reviewed.

2.2 Index Decomposition Analysis

In contrast to structural decomposition analyses, index decomposition analysis literature has produced a lot of different decomposition approaches with multiple indices over time. Generally spoken, an index is a certain weight that is allocated to a specific determinant (Hoekstra & van den Bergh, 2003). In the context of IDA, changes to the index drastically impact the results and have been the main point of development throughout the decomposition literature. The earliest proposals of index decomposition models relied on indices such as the *Laspeyres index* (base year weights), the *Paasche index* (terminal year weights), or the *Marshall-Edgeworth index* (mean of base and terminal year weights) (Madaleno & Moutinho, 2017). Later studies such as the ones by Boyd et al. (1987) and Reitler et al. (1987) then introduced decomposition models based on *divisia indices*. Using the divisia index method, the estimated effects that explain an indicator change are formulated in terms of the weighted average of logarithmic changes of the relevant variables (Ang & Choi, 1997). This index based on the weighted average of arithmetic changes is called the *conventional divisia index*. This conventional divisia index introduced by Boyd et al. (1987) and Reitler et al., (1987) has been used to study energy-induced emissions by Torvanger (1991), Lin and Chang (1996), and Ang and Pandiyan (1997), amongst others. However, all of the abovementioned index decomposition studies have two problems in common. First, using any of the abovementioned decomposition techniques will result in a residual, as the indicator change is not fully decomposed. As pointed out by Ang and Lee (1994), a large residual defeats the purpose of the decomposition analysis, as a great part of the observed indicator change will be left unexplained. The second issue, first mentioned by Liu et al. (1992), is the occurrence of zero values in the data. Decomposition analyses typically draw from highly disaggregated datasets with a multitude of industrial sectors, and oftentimes sectors have zero values for certain data, which in turn leads to computational problems for conventional models (Liu et al., 1992). Ang and Choi (1997) furthermore mention that the problem of zero values is particularly apparent when studying interfuel substitutions or energy-induced gas emissions. As the analysis in this thesis is concerned with energy-induced emissions, this problem is of high relevance and should be avoided. As such, the conventional divisa index decomposition, although being a valuable improvement to previous decomposition analyses, is not considered a suitable method for the research aim within this thesis. Fortunately, scholars set out to meet the challenges of zero values and residuals and derived improved decomposition models that alleviate these issues.

2.2.1 Logarithmic Mean Divisa Index (LMDI)

Trying to tackle the residual problem, Liu et al. (1992) and Ang (1994) introduced the *adaptive weighting divisia index* and proposed a general framework for decomposition formulation, thus significantly reducing the residual. However, even though their decomposition method led to smaller residuals, the zero-value problem still persisted under their framework. Consequently, Ang and Choi (1997) introduce a *refined divisia index* using a logarithmic weight function. This approach allows for a full decomposition of the observed indicator change by leaving no residual and can effectively handle zero values in the dataset (Ang & Choi, 1997). In their study, Ang and Choi (1997) decompose aggregate energy and gas emission intensities for the industry sector to evaluate the differences of the *conventional divisia index* to their proposed *refined divisia index* method. They conclude that the refined divisia index method based on a normalized logarithmic weight function is preferred to the conventional one with an arithmetic weight function, especially when dealing with highly disaggregated data on interfuel substitutions or emissions (Ang & Choi, 1997). The decomposition using the conventional divisia index is also called *Arithmetic Mean Divisia Index* (AMDI) decomposition, while the refined method is referred to as the *Logarithmic Mean Divisia Index* (LMDI) decomposition.

Nevertheless, even though solving the issues of residuals and zero values, the refined divisia index method proposed by Ang and Choi (1997) was criticized for not being consistent in aggregation (Ang & Liu, 2001; Ang, 2005). Instead of using the logarithmic mean weight function introduced by Vartia (1976) and Sato (1976), which the refined divisia index is based on, Ang and Liu (2001) propose a weight function where the logarithmic mean of the factorial value is divided by the logarithmic mean of the aggregate value[5]. By implementing this adjusted weight function to the existing LMDI model, Ang and Liu (2001) achieve a complete decomposition model without residuals that is able to handle zero values and is consistent in aggregation. As the model by Ang and Liu (2001), aside from the weight function, resembles the refined divisia index model of Ang and Choi (1997), a differentiation is made between the two LMDI models. The original model by Ang and Choi (1997) is referred to as LMDI II while the reworked model of Ang and Liu (2001) is referred to as LMDI I. Due to the desirable properties of the LMDI I model, this decomposition method is chosen for the analysis within this paper. The LMDI approach has furthermore been frequently applied by many scholars in emission-related disciplines, and as such has produced different determinants that can change emissions. In the next chapter, a closer look will be taken on what determinants emerged from the application of the LMDI model and how they are relevant for the determinants used within this paper.

2.3 Decomposition Determinants

As mentioned earlier, decomposition analysis in general is concerned with analysing the change of a given indicator between two points in time. The change in value of an indicator, such as emissions for instance, is reflected in determinants that explain this change. These determinants, or *effects*, represent the indicator change. Throughout the available literature, the LMDI approach has been used to analyse greenhouse gas emissions with respect to various of these determinants that potentially contribute to emission changes. Fernández González et al. (2014), for instance, differentiate between five decomposition determinants in their decomposition analysis of European CO_2 emissions. Their determinants include a population effect, a production per capita effect, a carbonization effect, a fuel mix effect, as well as an energy intensity effect (Fernández González et al., 2014). While varying between the respective European member countries, their study showed that one of the main drivers of aggregated CO_2

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[5] The weight function introduced by Ang & Liu (2001) can be formalized as w_i, where the numerator represents the logarithmic mean of the factorial value and the denominator the logarithmic mean of the aggregate value:

$$w_i = \frac{\frac{(C_i^T - C_i^0)}{(\ln(C_i^T) - \ln(C_i^0))}}{\frac{(C^T - C^0)}{(\ln(C^T) - \ln(C^0))}}$$

emissions appears to be the fuel mix effect, which is explaining emission changes due to changes in fuel consumption patterns. Moutinho et al. (2015) also analyse energy-related CO_2 emissions in Europe but differentiate between six effects that explain emission changes. Their effects include a carbon intensity effect, an energy mix effect, an energy intensity effect, a renewable productivity effect, as well as a capacity of renewable energy capita effect and a population effect. Their study concluded that the change in emissions was mainly driven by the energy mix effect, namely by switching to cleaner fuels for energy production (Moutinho et al., 2015). Interestingly, both papers state the fuel mix effect (or energy mix effect, respectively) to have a significant effect on emission changes. The calculation of this fuel mix effect, however, requires extensive data on the composition of energy sources and fuels that are consumed within an economy. As my analysis is differentiating emissions not only on a national level but on a sub-national sectoral level, this data would need to be available up to the sectoral level for all energy sources. Although such detailed data regarding energy sources exists (see for example IEA, 2021), it is either not free of charge or has to be drawn from a multitude of different data sources. Both approaches are considered problematic due to financial requirements that impede the reproducibility of results and a lack of data consistency, respectively. As such, the analysis within this paper will not draw upon data on fuel types and consequently will not include a fuel mix effect. However, other ways of examining the quality of the energy mix exist.

Cansino et al. (2015) use the LMDI I method to decompose changes in Spanish CO_2 emissions between 1995-2009. In their analysis, they decompose CO_2 emissions into five determinants. These determinants include a carbon intensity effect, an energy intensity effect, a structural change effect, an economic activity effect, as well as a population effect (Cansino et al., 2015). The study concluded that Spain is moving towards a low carbon economy that was made possible by improvements in carbon intensity and energy intensity, which offset the positive contributions to emissions coming from the economic activity effect and population growth (Cansino et al., 2015). Although the study by Cansino et al. (2015) has a different focus in terms of time scope and geography, the determinants to which emission changes are decomposed are the exact same ones that will be used within this paper. The reason for adopting these determinants for my own analysis is twofold. First, they include the most popular and widely acknowledged determinants of emission intensity (or carbon intensity, respectively), energy intensity, and structural change, which are present in a large majority of decomposition studies focusing on emissions (see for example Liu et al. 2007). These determinants allow to capture the quality of the energy mix from a GHG mitigation perspective (emission intensity effect), the change in energy efficiency and technology level (energy intensity effect), and the structural change happening in the economy (structural effect). Secondly, adding the determinants of economic activity and population allows the decomposition analysis to also capture income and population effects, respectively (Cansino et al., 2015). Most importantly, however, these five determinants directly relate to two of the most fundamental concepts in environmental research – the *IPAT* model and the *Kaya identity*. These two concepts have proven to capture the most fundamental forces of emission changes and have been at the root of many decomposition analyses throughout the past decades (see for example Ma & Cai, 2018; O'Mahoney, 2013). As the determinants used within my analysis strongly draw from the structure of these two concepts, they will be further explained in the next chapter.

2.3.1 Kaya Identity and the IPAT model

In general, the Kaya identity represents the relationship between man-made emissions and four kinds of relevant determinants. These determinants include the emission intensity, energy intensity, GDP per capita, and population (Kaya, 1989, Kaya & Yokobori, 1997). The relationship indicated by the Kaya identity is furthermore a renovated and mathematically more consistent version of the general IPAT model introduced by Ehrlich and Holdren (1971). This IPAT model is designed to indicate the driving forces of human impact and is an acronym for **I**mpact = **P**opulation x **A**ffluence x **T**echnology (Ehrlich & Holdren, 1971). The LMDI decomposition applied within this paper is using the scheme of an extended Kaya identity, as besides the aforementioned four determinants in the original Kaya identity I am also adding a determinant capturing the effect of structural change. As the Kaya identity is a reworked variation of the IPAT model, the determinants within the IPAT model can also be found in the determinants of my decomposition. Most clearly, the population effect of my decomposition directly relates to the population effect within the Kaya identity and the IPAT model. The energy intensity effect, moreover, is often used as an aggregate proxy for the energy efficiency or technology level of an economy (Cansino et al., 2015), thus representing the technology part within the IPAT model. Additionally, the economic activity effect depends on the GVA per capita and captures income effects on emission changes, hence representing the affluence part within the IPAT equation (Cansino et al., 2015).

LMDI decomposition methods based on an extended Kaya identity have received wide recognition within energy and environmental studies and have been employed by a variety of scholars. O'Mahoney (2013), for instance, used such a model to decompose Ireland's carbon emissions from 1990 to 2010 and found that scale effects of affluence and population growth increased Irish emissions and are countered by energy intensity and fuel substitution effects. Zhang et al. (2017) furthermore apply an extended LMDI model to decompose China's industrial CO_2 emission intensity and industrial CO_2 emissions. In doing so, they extend the LMDI framework to include eight determinants. These determinants include effects of the energy emission factor, energy intensity, process carbon intensity, R&D efficiency, R&D intensity, investment intensity, industrial structure, as well as emission intensity (Zhang et al., 2017). After combining the LMDI data with different simulation scenarios, they conclude that the most important factors facilitating a decrease in emission intensity are R&D intensity and energy intensity, while investment intensity is a major driver of emission intensity (Zhang et al., 2017). Although many of the effects mentioned in their study are not relevant for the analysis within this paper, it is a great piece of research to showcase the extension potential of LMDI and the varying effects that are investigated throughout the available literature. Now that the origin of the five determinants used within this thesis has been discussed, a closer look needs to be taken on the time application of the LMDI model.

2.4 Application of LMDI

Aside from different determinants that are being examined, decomposition analyses have also been applied to time and sector-specific contexts. Authors such as Liu et al. (2007), for example, utilized LMDI to decompose China's industrial CO_2 emissions into five determinants. Their determinants include an activity effect, an energy intensity effect, a fuel mix effect, an emission coefficient effect, as well as a structural change effect. They found the overwhelming contributors to the change of CO_2 emissions in China's industrial sectors to be the industrial activity effect as well as the energy intensity effect. Although focusing on China instead of a European country, the discussed paper by Liu et al. (2007) shares some important methodological characteristics that are important for the analysis conducted within this paper. First, the authors focus on only one country instead of a region or group of countries and in doing so focus on thirty-six industrial sectors. This allows for the decomposition results to not only provide information on the overall effect of each determinant on the emission change, but also on the effect of each economic sector on the emission changes. This methodology enabled Liu et al. (2007) to conclude that three sectors of the economy accounted for 59.31 percent of total increased industrial CO_2 emissions. Similarly, I am dividing the economy of Belgium into six sectors to evaluate which sectors play the most important role in emission changes. Secondly, Liu et al. (2007) perform a time series decomposition instead of a period-based decomposition. Many authors decompose emission changes based on periods with two benchmark years where the in-between years are discarded. Using time series decomposition, however, is considered superior to period-wise decomposition techniques (Ang & Lee, 1994; Ang 1994), as it better explains the underlying mechanisms of emission changes. Likewise, the emission decomposition within this paper will first examine emission changes using time series decomposition and later aggregate the observed years into two distinct time periods relating to the commitment periods of the Kyoto Protocol. Aside from more accurately showcasing the underlying mechanisms of emission changes, this approach will furthermore allow for a comparison between time series and period-wise decomposition of emission changes. Next, studies who have applied a LMDI model in the context of the Kyoto Protocol are discussed.

2.4.1 LMDI and the Kyoto Protocol

In their 2007 paper, Diakoulaki and Mandaraka perform a decomposition analysis within the EU manufacturing sector for the time period between 1990 and 2003. Similar to this thesis, they look at a time interval of less than fifteen years and split this interval into two distinct time periods for assessing the emission progress prior and past the agreement of the Kyoto Protocol (Diakoulaki & Mandaraka, 2007). The aim of their methodology was to assess the real effort undertaken in each European country prior and after the commitments made by signing the Kyoto Protocol. Overall, the study concluded that most EU countries made a considerable but not always sufficient decoupling effort, and that no significant acceleration can be observed in the post-Kyoto period (Diakoulaki & Mandaraka, 2007). However, these results are to be taken with a grain of salt. Even though Diakoulaki and Mandaraka (2007) are relating their distinct time periods to the signing of the Kyoto Protocol in 1997, they are not considering the commitment periods as established within the Kyoto Protocol. Instead, they differentiate between a time interval prior to the signing of the Kyoto Protocol in 1997 and a time interval after the signing in 1997. Given that the first commitment period starts in 2008 only (United Nations, 1998), it is questionable whether countries start showing real efforts towards emission reductions before that, even more so as by 1997 the Kyoto Protocol was not yet in effect. This means that an emission decomposition relating to a pre and post Kyoto time period should split the time periods by the date the Kyoto Protocol became effective, as real efforts in cutting emissions is not expected to begin before the ratification of the Kyoto Protocol.

Later studies, such as the one by Moutinho et al. (2015) set out to do exactly that. Within their analysis, they examine the differences in European CO_2 emissions during two time periods pre and post the 2005 ratification of the Kyoto Protocol. In contrast to the study by Diakoulaki and Mandaraka (2007), they find significant improvements in emission reductions from the pre-Kyoto period to the post Kyoto period. They find that these improvements mainly stem from changes to the energy mix and switching to cleaner fuels for end-user energy production (Moutinho et al., 2015). However, even though their study provides insights as to what drove European emission reduction after the ratification of the Kyoto Protocol, they do not examine the commitment periods of emission reduction as established by the Kyoto Protocol. Moreover, Moutinho et al. (2015) base their analysis not on sectoral data but on national data that is later aggregated to regional areas relating to Southern, Northern, Eastern, and Western Europe. As such, even though between country differences are clearly presented, a more detailed look into the sectoral emission developments is missing. In the next chapter, I will review the developments and findings of previous decomposition literature with regards to Belgium.

2.5 LMDI decomposition in Belgium

As shortly touched upon before, the decomposition literature for Belgium is limited. Only a few studies are focusing on Belgium specifically, whereas most entail Belgium as part of a broader study of multiple countries. Some scholars, such as Moutinho et al. (2018), have decomposed carbon emissions for a specific subgroup of countries that entailed Belgium. In their study, they applied a LMDI decomposition to decompose carbon emissions into six effects[6] for the time period from 1985 to 2011. They find that one of the main effects leading to carbon emission

[6] The six effects examined in Moutinho et al. (2018) include: carbon trade intensity, fossil fuels trade effect, fossil fuel intensity, renewable source productivity, the financial power of electricity effect, and financial development effect.

changes in Belgium during the observed period were changes in renewable productivity (Moutinho et al., 2018). However, the focus of the study was not on Belgium particularly and as such the results for Belgium were used for comparing purposes more than for interpreting the results in Belgium specifically. Similarly, Fernández González et al. (2014) tracked European CO_2 emissions through LMDI decomposition. In doing so, they apply three different approaches and differentiate between eight effects in total[7]. The five main effects entailed a population effect, a carbonization effect, a production per capita effect, as well as an energy intensity effect and as such are based on an extended Kaya identity. The study concludes that for Belgium, changes in the fuel mix and energy intensity have been the main driving forces of CO_2 reductions (Fernández González et al., 2014). However, Belgium is again studied only on a comparative basis together with other European countries and no detailed analysis of its sectoral emission contribution is provided.

In a previous approach by Albrecht et al. (2002), a Shapley decomposition of carbon emissions between 1960 and 1996 is applied to four countries, including Belgium. This Shapley decomposition method was introduced by Albrecht et al. (2002) and is based on the so-called Shapley value introduced by Shapley (1953) and is intended to result in a perfect decomposition. Although it is another approach of decomposing emission changes, its anticipation in recent literature has been limited and it is considered inferior to the LMDI approach discussed before. The Shapley decomposition applied within Albrecht et al. (2002) is based on the Kaya identity and differentiates between nine components. Those components include three carbon intensity effects, three energy intensity effects, the effect of per capita GDP, as well as the population effect (Albrecht et al., 2002). The results indicate that for the observed period there was almost no structural effect in Belgium, whereas the strongest drivers of carbon emissions appeared to be carbon intensity and energy intensity (Albrecht et al., 2002). However, even though this study explains the determinants of emission changes in Belgium a bit more detailed than the two papers discussed before, its ultimate purpose was to showcase the advantages of the Shapley decomposition in comparison to conventional decomposition approaches instead of interpreting the results specifically for Belgium.

Another one of the few decomposition analyses focusing solely on Belgium is provided by Hambÿe et al. (2018). In their study, they use SDA to compare carbon footprint results between two different datasets. They use the classic multiregional input-output (MRIO) tables provided by the World Input-Output Database (WIOD) as well as a modified input-output table where they replaced the source data for Belgium used in the WIOD MRIO tables by supply and use

[7] The amount of effects that carbon emission changes are decomposed to depends on the approach that is applied within Fernández González et al. (2014).

tables from national sources (Hambÿe et al., 2018). Moreover, their SDA differentiates between an emission intensity effect, the effect of input structure, as well as a final demand effect[8]. However, these effects are not used to determine the driving forces of emission changes in Belgium, but to rather serve as a base of comparison between the two different data sources. As such, even though applying SDA specifically to the case of Belgium, the analysis of Hambÿe et al. (2018) differs from the present thesis in scope as well as in purpose.

Finally, a study by Michel (2013) is worth mentioning. In this study, Michel (2013) aims at highlighting contributions to Belgian emission changes in manufacturing from offshoring. The chosen methodology to achieve this aim combines elements of both SDA and IDA, although the SDA elements are significantly more relevant than the IDA elements. Using this combined method, Michel (2013) decomposes emission changes as well as changes in emission intensity. Consequently, the amount and type of determinants that are being differentiated depends on the indicator that is being decomposed. For changes in emissions, Michel (2013) differentiates only between a scale (economic activity) effect as well as an intensity effect, whereas changes in energy intensity are decomposed into a between effect and a within effect[9]. The results obtained indicate that the scale effect positively contributed to air emissions but was offset by the strong negative contribution of the intensity effect. Similar to the other studies discussed in this chapter, the focus of the paper by Hambÿe et al. (2013) is specifically on highlighting the impact of the offshoring effect on manufacturing in Belgium. As such, although decomposing air emission changes in Belgium, the study differs significantly from the present paper in terms of focus and methodology. Overall, the emission decomposition literature in Belgium remains scarce and very specific to particular determinants that are being analysed.

[8] It should be noted that Hambÿe et al. (2018) further split the three main effects into multiple other subcategories of effects that fall into the broader categories of the three effects of emission intensity, input structure and final demand.

[9] The within effect in Michel (2013) is indicating the contribution of changes in emission intensities for domestic intermediates while the between effect is measuring the impact due to a shift in the industry composition of output. Additionally, the within effect is further split into a technique effect, an efficiency effect, as well as an offshoring effect.

2.6 Literature Gap

After having discussed relevant developments in emission and decomposition research, as well as primary findings, I will now briefly discuss the literature gap this study intends to fill. As touched upon in the introduction, analysing the underlying determinants of emission changes in Belgium poses a highly interesting and valuable field of research. Yet, when looking at the available literature, surprisingly little is found. In fact, to the best of my knowledge, there exists not a single paper utilizing LMDI to decompose GHG emission changes in Belgium with a focus on isolating the determinants and sector contributions to emission changes. Additionally, although there exist multiple decomposition studies relating to pre and post Kyoto Protocol periods, I failed to find a decomposition analysis focusing specifically on the actual commitment periods established within the Kyoto Protocol. Hence, this study is intended to fill this literature gap by providing the first LMDI application focused on sectoral GHG emissions in Belgium and putting the decomposition results in the context of the two commitment periods of the Kyoto Protocol. As such, this study contributes to the existing emission decomposition research by providing a better understanding of the driving forces and contribution of sectors to GHG emissions in Belgium. Moreover, this study aims at adding a valuable perspective to the existing literature in terms of retracing what drove emission changes during the two commitment periods of the first international and binding agreement on climate protection. In the next chapter, I will begin with discussing the data sources used for my analysis.

3 Data

Within this section, the process of data acquisition and data validation is explained and a critical reflection on the quality and reliability of data is pursued. The method of decomposing emission changes in Belgium between 2008 and 2018 requires extensive data on the sectoral distribution of gross value added, greenhouse gas emissions, energy use, as well as population. This data is at the very root of the analysis and represents the raw input data needed to proceed with decomposing emission changes. Notably, the analysis conducted within this paper aims for a better understanding of the sectoral development of emissions in Belgium during the commitment phases as established by the Kyoto Protocol. As such, it is not enough to just look at data for the whole economy as a total. Instead, the values for gross value added, greenhouse gas emissions, energy consumption, and population need to be available at a detailed sub-national level. Additionally, it is imperative for the data to be consistent to produce reliable and conclusive results for the decomposition analysis. Varying data sources differ strongly in their allocation mechanisms of economic activities, especially when it comes to the sectoral allocation of environmental indicators such as energy consumption or greenhouse gas emissions. Ensuring consistency of data is hence particularly important, even more so as I am only using secondary data sources.

It was thus considered beneficial to the analysis to minimize the variety of data sources. In fact, all data that is used as input for decomposing emission changes with the LMDI I method is drawn from Eurostat. Being the statistical office of the European Union and responsible for publishing high-quality statistics and indicators for comparisons between countries and regions, Eurostat is considered a highly reliable and trustworthy source of data. This quality of data is further ensured by the fact that Eurostat develops harmonised definitions, classifications and methodologies for the production of official statistics and closely cooperates with national statistical authorities (European Commission, 2021b). Additionally, many of the input variables needed for my decomposition analysis are collected through mandatory data collection within the European Union, thus further manifesting the quality of the data. For the purpose of decomposing emission changes in Belgium from 2008 to 2018, four datasets published by Eurostat are of relevance. These datasets contain official statistics regarding the sectoral distribution of gross value added, greenhouse gas emissions, energy consumption, and population. The title, data code, as well as last update date of the datasets that are being used for the present decomposition analysis are presented in the table below.

Table 1: Eurostat data sources

	Gross Value Added	*GHG Emissions*	*Energy Consumption*	*Population*
Title:	National accounts Aggregates by industry (up to NACE A*64)	Air emission accounts by NACE Rev. 2 activity	Energy supply and use by NACE Rev. 2 activity	Population on January 1 by age group and sex
Code:	nama_10_a64	env_ac_ainah_r2	env_ac_pefasu	demo_pjan
Last update:	06/05/2021	10/03/2021	08/02/2021	27/04/2021

Source: author illustration

As can be seen above, the data used is recently updated and is drawn from four separate datasets containing secondary data collected and maintained by Eurostat. Since the data is drawn from four different datasets, it is important to ensure a consistent was of allocating each of the four input variables to the same sectors and industries across the different datasets. One important aspect of my analysis is that I want to depict the total emission footprint of the Belgian economy, while still being able to differentiate between the most important economic sectors. Moreover, I am interested in depicting the economy with only six sectors as this significantly eases result interpretation while still maintaining a reasonable level of sectoral differentiation. As such, a reference framework for the aggregation of economic activities is needed. A widely known and anticipated framework for doing so has been developed by the European Union and is known as the *European Classification of Economic Activities* (NACE) framework. This reference framework is further discussed in the next chapter.

3.1 The NACE framework

The Statistical Office of the European Communities (2006, p. 6) states that “NACE is the acronym[10] used to designate the various statistical classifications of economic activities developed since 1970 in the European Union”. The use of this system is mandatory within the European Statistical System and allows for comparability at the world level of statistics, as NACE is part of an integrated system of statistical classifications developed under the auspices of the United Nations Statistical Divisions (Statistical Office of the European Communities, 2006, p. 6). In general, NACE is derived from the United Nations’ *International Standard Industrial Classification* (ISIC) of all economic activities. Both frameworks aim at explaining a given economy in economic activities and sectors. However, even though having the same sector items at the highest levels, NACE is more detailed at lower levels of economic activities. The coding structure of the NACE reference framework is organized in four different aggregation levels that are described in Figure 1 below (Eurostat, 2008, p. 15).

Figure 1: Structure and Coding of the NACE reference framework

i. A first level consisting of headings identified by an alphabetical code (sections)

ii. A second level consisting of headings identified by a two-digit numerical code (divisions)

iii. A third level consisting of headings identified by a three-digit numerical code (groups)

iv. A fourth level consisting of heading identified by a four-digit numerical code (classes)

Source: Eurostat, 2008, p. 15

[10] NACE is derived from the French title "**N**omenclature générale des **A**ctivités économiques dans les **C**ommunautés **E**uropéennes" (Statistical classification of economic activities in the European Communities) (Statistical Office of the European Communities, 2006)

While the first level based on sections represents the broadest classification of activities, the fourth level represents the most detailed one. In general, the sections are coded in alphabetical order while divisions, groups and classes are coded numerical. Notably, the section level code is not integrated in the NACE code that identifies the division, group and class of a given activity (Eurostat, 2008). The activity “Manufacture of glues”, for instance, is identified by the code 20.52, where 20 is the code for division, 20.5 the code for the group level, and 20.52 the code for the class (Eurostat, pp. 15-16). On the section level the activity “Manufacture of glues” belongs to section C, which is however not indicated in the code 20.52. Moreover, it is worth mentioning that some number gaps exist in the numerical coding of economic activities. This is a conscious decision by the NACE creators to allow the introduction of additional divisions without having to change the complete NACE coding system (Eurostat, 2008). Aside from the four coding levels within the NACE classification system, there also exist four levels of hierarchy that structure economic activities based on different level aggregates of activities. At the broadest level, the A*10 hierarchy is applied, followed by the more detailed A*21 and A*38 hierarchies, where the number behind the asterisk always indicates the number of economic activities present in the respective hierarchy. The most detailed hierarchy is called A*64 and differentiates between sixty-four economic sectors. A full overview of the structure of this system is provided by the OECD and can be observed in Appendix A.

As mentioned earlier, I will differentiate between six economic sectors within the analysis in this paper. However, as my goal is to analyse and depict the full economy of Belgium, I need to aggregate economic activities of a more detailed level into the broader six sectors that I am analysing. Hence, I group economic activities into broader sectors based on the division coding of the NACE reference system (see Figure 1). Each of the six final sectors thus consists of various division activities present in the A*64 hierarchy of economic activities, allowing the full economy to be represented within the six sectors. An overview of the classification system used for aggregating the final six sectors is provided in Table 2 below.

Table 2: Sectoral aggregation of NACE Rev. 2 divisions

	Agriculture	*Industry*	*Energy*	*Services*	*Transport*	*Residential*
NACE Rev. 2 A*64 divisions entailed in the sector	01, 02 and 03	05, 06, 07, 08, 09, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 41, 42 and 43	19 and 35	33, 36, 37, 38, 39, 45, 46, 47, 52, 53, 55, 56, 58, 59, 60, 61, 62, 63, 64, 65, 66, 68, 69, 70, 71, 72, 73, 74, 75, 77, 78, 79, 80, 81, 82, 84, 85, 86, 87,	49, 50, and 51	97 and 98

				88, 90, 91, 92, 93, 94, 95, 96 and 99.		

Note: see Appendix A for a full breakdown of NACE Rev. 2 divisions and hierarchies, *Source*: author illustration

As can be seen in the above table, all sectors defined within this thesis entail multiple divisions. As such, the total values reported for each of the six sectors represent the sum of the values of all divisions entailed in the respective sector. Notably, the aggregation of divisions into the six broader sectors is not arbitrary or by random selection. Instead, the divisions were aggregated to the six sectors based on the methodology that was used for the construction of the Eurostat energy balance (Eurostat, 2019, pp. 31-34). In general, the energy balance published by Eurostat is the most complete statistical accounting of energy products and their flow in the economy (Eurostat, 2019, p. 3). While not being of relevance for this thesis from a data point of view, the energy balance provided by Eurostat aggregates economic activities into multiple broader sectors that closely relate to the ones being used within this thesis. It should be noted, however, that the economic activities within the energy balance are aggregated using the very detailed third and fourth coding level of the NACE reference framework (see Figure 1). This means that some sectors in the energy balance contain only certain groups or sub-classes of an economic activity, which relate for example to specific energy products or fuel types. Notably, the aggregation of sectors within this paper is not considering variations in that much detail. As such, only the second coding level based on divisions is used to aggregate the economic activities into broader sectors. Nevertheless, the six sectors within this thesis relate directly to the ones used for aggregation in the energy balance, with only a few exceptions. The sectors that were aggregated in the exact same way as in the energy balance include the Transport sector and the Residential sector (see Table 2). However, due to the higher degree of detail in the aggregation of the energy balance methodology, there are some minor differences in the aggregation of the Agriculture sector, the Industry sector, the Services sector and the Energy sector. These differences are shortly outlined below.

3.1.1 The Agriculture Sector

The Agriculture sector within this paper is an aggregate of the NACE Rev. 2 Divisions 01, 02 and 03. Notably, the Eurostat energy balance differentiates between an Agriculture & Forestry (Divisions 01 and 02) sector as well as a fishing sector (Division 03). The reason that I add Division 03 to the Agriculture sector is twofold. First, on a broader level of the NACE hierarchy, such as A*21 or below, these three divisions are put together into one section with the same alphabetical code A (see Appendix A). Secondly, fishing ultimately serves the same purpose as agriculture in generating a source of food. As I want to keep the number of sectors within my analysis at a reasonable yet fairly detailed level, I decided to add NACE division 03 to the Agriculture sector instead of treating it separately.

3.1.2 The Industry Sector

The Industry sector within this paper is an aggregate of the NACE Rev. 2 Divisions 05, 06, 07, 08, 09, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 41, 42 and 43. Again, as I only differentiate between activities up to the division level, there are groups and classes that are part of the industry sector within this paper but not part of the industry sector of the energy balance. The first difference can be found in division 24. The industry sector within the energy balance includes only the NACE Rev. 2 groups 24.1, 24.2, 24.3 and 24.4, as well as the classes 24.51, 24.52, 24.53 and 24.54. The reason that the energy balance is not including all of division 24 into the industry sector is its differentiation between activities that belong to final consumption and those who serve as an intermediate input or output (Eurostat, 2019). As I am only interested in the emission relevant use of energy per sector and not its role in the overall energy flow, the differentiation based on groups or classes of division 24 is not necessary for my analysis. The same logic applies to divisions 07, 08 and 09, where the energy balance excludes classes 07.21 and 08.92 from the industry sector and only takes into account class 09.9 of division 09. In the present thesis, the full divisions of 07, 08, 09 and 24 are part of the industry sector. Aside from these particular groups and classes, the divisions entailed in the industry sector within this thesis exactly match the ones used for the aggregation within the energy balance.

3.1.3 The Energy Sector

The energy sector within my analysis is arguably the sector with the largest difference when compared to the energy balance. Within the energy balance, the energy sector is treated as a medium block and not as a final consumption block and includes the NACE Rev. 2 divisions 05, 06, 19 and 35, as well as the group 09.01 and the NACE Rev. 2 classes 07.21 and 08.92. Again, the reason for only including particular classes of a given division is the energy balances' differentiation between transformation inputs, transformation outputs, and final consumption. Since this differentiation is not relevant for my analysis, the energy sector within this paper will only include division 35 and 19. As mentioned before, divisions 05, 06, 07, 08 and 09 are part of the Industry sector within this thesis. Consequently, the NACE Rev. 2 classes 07.21 and 08.92 as well as group 09.01 are also part of the Industry sector instead of the Energy sector.

3.1.4 The Service Sector

The Service sector within this paper consists of the NACE Rev. 2 divisions 33, 36, 37, 38, 39, 45, 46, 47, 52, 53, 55, 56, 58, 59, 60, 61, 62, 63, 64, 65, 66, 68, 69, 70, 71, 72, 73, 74, 75, 77, 78, 79, 80, 81, 82, 84, 85, 86, 87, 88, 90, 91, 92, 93, 94, 95, 96 and 99. Except for a single class, these divisions correspond exactly to the ones used for the aggregation of the Service sector within the energy balance. The one class that is not included in the Service sector of the energy balance is class 84.22, which includes military fuel use for all mobile and stationary combustion (Eurostat, 2019, p. 34). This class is part of division 84, representing public administration and defence as well as compulsory social security activities (see Appendix A). Within the energy balance, class 84.22 is part of a sector that is not elsewhere specified (Eurostat, 2019).

Considering I am aiming for a full emission decomposition, it is not desirable for my analysis to have non-specified sectors consisting of only one particular class. As such, given that division 84 clearly belongs to public services, class 84.22 is treated as a part of the Service sector within this paper as well. After having discussed the aggregation techniques used for composing the final six sectors, I will now further discuss the data that is being allocated to the six sectors that were just defined. As shortly touched upon before, this data includes the gross value added (GVA), greenhouse gas emissions, energy use, as well as population of Belgium for all years between 2008 and 2018.

3.2 Gross Value Added

The data for Gross Value Added (GVA) is provided by Eurostat and is drawn from the *National accounts Aggregates by industry (up to NACE A*64)* dataset (see Table 1). In general, this dataset contains detailed breakdowns of main GDP aggregates by industry and consumption purpose and covers the European Union, the euro area, EU member states, the EFTA (European Free Trade Association) countries and Candidate countries (Eurostat, 2021). National accounts provide an overall picture of the economic situation and are a coherent and consistent set of macroeconomic indicators, which are widely used for economic analysis and forecasting, policy design and policy making (Eurostat, 2021). For the decomposition analyses conducted within this paper, the gross value added of each of the sixty-four NACE activities was the variable of interest. The unit of measure for this type of GVA data was chosen to be constant *2015 chain linked volumes of million euro*. Using chain linked volumes for the analysis is valuable for two reasons. First, chain linked volumes are less sensitive to extreme values that might occur in some years. For example, if current prices of million euro are chosen as the unit of measure, extreme values may become problematic as they have the potential to significantly alter the results of the analysis depending on the year that is chosen. Second, chain linked volumes allow for different currencies to be converted to the same unit. As such, using chain linked volumes of million euro allows for a much better comparability across countries if the results of the analysis are to be put into context with those of other countries with varying national currencies. The data for gross value added entailed in the annual national accounts is furthermore compiled in accordance with the European System of Accounts (ESA 2010), which is the newest internationally compatible EU accounting framework for a systematic and detailed description of an economy (Eurostat, 2021; Eurostat, 2013). The final gross value added data compiled for the six sectors of the decomposition analysis within this paper can be observed in Appendix B.1. Within the decomposition analysis, gross value added is indicated by the letter Q.

3.3 Greenhouse Gas Emissions

The data for greenhouse gas emissions is again provided by Eurostat and can be found in the *Air emission accounts by NACE Rev. 2 activity* dataset (see Table 1). This dataset reports the emissions of greenhouse gases and air pollutants broken down by sixty-four industries classified according to NACE Rev. 2 (Eurostat, 2021b). In general, air emission accounts are a subset of environmental-economic accounts and record flows of gaseous and particulate materials that are emitted to the atmosphere as a result of economic productivity (Eurostat, 2021b). The greenhouse gas emission data within the dataset is compiled by National Statistical Institutes (NSI) and is submitted to Eurostat through annual mandatory data collection. This collection of data includes an electronic questionnaire with regards to data collection methods as well as a quality report, again highlighting the strong data quality standards employed by Eurostat. While the dataset reports values for more than ten different air pollutants across economic sectors, I am focusing on greenhouse gas emissions in general. Focusing on GHG instead of just a particular air pollutant, such as CO_2 for example, has two main benefits. First, GHG's entail emissions from various air pollutants and as such incorporate emissions from multiple gaseous and particulate substances. As such, they provide a much more complete picture of the actual emission situation within a country compared to when only focusing on a particular air pollutant. Second, using GHG as the emission indicator enables a more balanced perspective on the released emissions within an economy, as not all sectors have similar shares of air pollutants. The transport sector, for example, has been found to be responsible for almost two thirds of all nitrogen oxides (NO_x) emissions within Europe (EEA, 2021). Similarly, the German Federal Environmental Agency states that air polluting Ammonia (NH_3) mainly comes from agriculture while non-methane volatile organic compounds (NMVOCs) mainly arise from the use of solvents in industrial processes (Umweltbundesamt, 2020). As such, the share of different pollutants strongly differs across economic sectors and focusing on only one pollutant would inevitably lead to a skewed picture of the actual emission distribution within a given economy. Within greenhouse gases, all air pollutants are represented as their respective CO_2 equivalents, thus capturing the full emission footprint of an economy and its sectors. These GHG emissions in form of CO_2 equivalents are reported in thousand tonnes. The emissions have been allocated to their respective economic activities based on the NACE Rev. 2 classification framework and were aggregated to broader sectors in accordance with the economic activity allocation presented in Table 2. The final data for greenhouse gas emissions in thousand tonnes for each of the six sectors within my analysis can be found in Appendix B.2. Within the decomposition analysis, greenhouse gas emissions are indicated by the letter *C*.

3.4 Energy Use

The data used for energy consumption is drawn from the *Energy supply and use by NACE Rev. 2 activity* dataset from Eurostat. This dataset is part of the broader physical energy flow accounts (PEFA), representing one module of the European environmental-economic accounts

(Eurostat, 2020). PEFA accounts are conceptually rooted in the international statistical standard *System of Environmental-Economic Accounting (SEEA)* (United Nations, 2021b). Moreover, PEFA accounts are also compliant with internationally established concepts and definitions for energy statistics from the *International Recommendations for Energy Statistics (IRES)* (United Nations, 2018). Within physical energy flow accounts, such as in the one being used for the decomposition analysis within this paper, three concepts are essential to note. First, a differentiation between three generic types of energy flows as suggested in the SEEA is established. These three energy flows are 1) *natural energy inputs*, 2) *energy products*, and 3) *energy residuals* (United Nations, 2014). The first of these flows, natural energy inputs, captures flows from the environment into the economy, such as fossil energy carriers and kinetic energy in form of wind or geothermal heat for example (Eurostat, 2021c). Energy products on the other hand are output flows from production processes that occur within the economy and are typically produced by extractive industries such as power plants or refineries (Eurostat, 2021c). Lastly, energy residuals are mainly energy in form of dissipative heat arising from the end use of energy products, flowing from the economy into the natural environment (Eurostat, 2021c). For the decomposition analysis within this paper, I chose to consider all three types of energy flows instead of just focusing on one. This will result in the most complete set of energy that is ultimately consumed by economic activities.

The second important concept relevant for PEFA accounts is that the accounting framework of supply and use tables established in national accounts and the *System of Environmental-Economic Accounting* (SEEA) is kept for coherency. This means that energy use is accounted for in accordance with the same concepts as in the SEEA. Third, the energy flows within PEFA accounts follow the residence principle as established by the SEEA, meaning that energy flows are assigned in relation to the resident unit's activities, regardless of where the energy use occurs geographically (Eurostat, 2021c). That way, it can be ensured to also include the energy use of Belgian activities that is not being consumed domestically. Furthermore, the *Energy supply and use by NACE Rev. 2 activity* dataset allows to differentiate the energy flows based on supply, transformation use, (end) use, as well as emission-relevant use. For the analysis conducted within this paper, *emission-relevant use of energy* was chosen as the variable of interest. Although emission-relevant use mainly entails energy products, it is referring to the combustive use of all three types of energy flows, thus capturing the full effect of energy use that is relevant for emissions. In general, the definition of emission-relevant use is confined to processes of combustion and is derived from guidelines established for the compilation of emission inventories (European Comission, 2018). This means it refers to fossil fuel combustion processes delineated and recorded in emission inventories under the CRF/NFR[11] source code 1.A (European Comission, 2018, p. 13). Overall, the data that is drawn for the energy use variable is the emission-relevant use of energy, considering the energy flows of natural energy inputs, energy products, and energy residuals. All values are reported in Terajoule (TJ) and available for each of the sixty-four economic sectors as established by NACE Rev. 2. As such, the final energy consumption value reported for each of the six sectors within my analysis represents the sum of the values of all respective sub-divisions entailed in that sector (see Table 2). The final values for energy use per sector in Belgium between 2008 and 2018 are reported in Appendix B.3. Within the decomposition analysis, the variable of energy use is indicated by the letter *E*.

3.5 Population

The population data used as input to the decomposition model has been drawn from the *Population on 1 January by age and sex* dataset from Eurostat (see Table 1). The dataset is part of the larger population and migration statistics and reports the number of inhabitants of a given area on January 1 of the year in question (Eurostat, 2021d). The term population in this context refers to the *usually resident population*. This usual residence principle is referring to the place where a person normally spends the daily period of rest, regardless of temporary absences (Eurostat, 2021d). In the present dataset, this includes those who have lived in their place of usual residence for a continuous period of 12 months before reference time and those who arrived in their place of usual residence during the 12 months before the reference time with the intention of staying there at least for one year (Eurostat, 2021d). Typically, member states send the population data to Eurostat on the 31 December of the reference year under Regulation No. 1260/2013 (European Parliament, 2013), which is then conventionally published by Eurostat on the 1 January of the following year (Eurostat, 2021d). In this context it should be noted that the collection and report of population data by age, sex, and region is mandatory for member states since 2014 (Eurostat, 2021d). From an application point of view, the data on

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[11] CRF/NFR are internationally harmonised classifications for emission sources employed by air emission inventories. Common Reporting Format (CRF) is applied in greenhouse gas inventories under the UN Framework Convention on Climate Change. Nomenclature for Reporting (NFR) is applied in inventories for air pollutants under the UNECE Convention on Long-Range Transboundary Air Pollution. (European Commission, 2018, p. 13).

population needs to be available only on the country level, not on the sector level. The reason for this is that the population data is only used for the calculation of the GVA per capita as well as for analysing the change from one year to another. As such, a sectoral differentiation of population is not needed. The final values for the population in Belgium between 2008 and 2018 are provided in Appendix B.4. Within the decomposition analysis, population is indicated by the letter *P*. After now having discussed the different data sources and compilation techniques used to arrive at the final data values, the next part of this paper will illustrate the methodology applied to decompose GHG emission changes.

4 Methodology

In general, the methodology discussed within this chapter is designed in a way that is considered to answer the stated research questions in the best possible way. While the first research question is focused on a better understanding of the general development of the driving forces of emission changes in Belgium from 2008 to 2018, the second question is more specifically focusing on the two commitment periods of the Kyoto Protocol and how the contribution of the determinants and economic sectors differs between the two commitment periods. The intuition behind the phrasing of the research questions was to produce holistic results that showcase not only the general development of emission determinants and sectors in Belgium throughout time, but also to put them into the context of the first legally binding climate protection agreement. In line with this twofold research aim, the decomposition analysis within this paper will be conducted in two steps. The first step is a time-series analysis, where I decompose the emission changes of Belgium from each year to the next one for all ten years that are being observed. This will produce results that indicate the contribution and development of each determinant and economic sector on a yearly basis between 2008 and 2018. In the second step, this time series data is then aggregated into two distinct time periods from 2008-2012 and from 2013-2018, with each one relating to a commitment period of the Kyoto Protocol. By doing so, the second research question can be answered, and valuable insights can be drawn as to what determinants and economic sectors were most relevant for reducing GHG emissions in Belgium during the commitment periods of the Kyoto Protocol. Additionally, as pointed out by Ang & Lee (1994), the aggregation of time series decomposition data into periods has the advantage of not discarding the in-between years of a given time period, which is sometimes the case for decomposition analyses. However, before starting with the actual decomposition, the first step is to handle the zero values present in the data.

4.1 Zero Values

After ensuring a sectoral aggregation methodology that allows me to represent the Belgian economy with just six sectors, the next step of my analysis is to process the data for each of those six sectors. As shortly touched upon before, all values that are reported for each of the six sectors are the sum of the values reported for all divisions entailed in the respective sector. Unfortunately, as already pointed out by Liu et al. (1992), highly disaggregated data often contains zero values. As the data I use for my analysis stems from highly disaggregated datasets that differentiate between sixty-four economic activities, the occurrence of zero values is rather likely. As such, a solution needs to be identified on how to deal with those zero values. Ang (2005) suggests dealing with this issue by replacing all zero values in the data by a small positive constant between 10^{-10} and 10^{-20}. Notably, the final six sectors in my analysis are aggregates of a multitude of divisions. This means that a given sector in my analysis can only take on the value of zero if all divisions entailed in the sector have the value zero, which is a scenario that is rather unlikely. Nevertheless, there exist potential zero values on a divisional level and those need to be taken care of. As such, the next step of my analysis after defining the sectoral structure is to replace all zero values in my data sets by the small positive constant of 10^{-15}. Even though the difference from using a small positive constant to simply using zero as a value is marginal on the aggregate level, I still choose to replace zero values for the theoretical case of decomposing emission changes on a more disaggregated divisional level to ensure methodological coherency. After augmenting the data to not include any zero values, I begin with applying the LMDI model to decompose GHG emission changes.

4.2 Multiplicative LMDI model

The nature of the research questions requires a detailed analysis of population, sectoral energy use, GHG emissions and value added per sector to be answered. Additionally, the driving forces of GHG emission changes across industries need to be isolated to measure their impact on emission changes. The method chosen for this analysis is the multiplicative logarithmic mean divisia index (LDMI I) method as presented by Ang and Liu (2001). As already pointed out in the theory section, there are multiple benefits this method offers in comparison to other index decomposition analyses linked to different indices or structural decomposition analyses (SDA). From an application perspective, the main advantage in comparison to other methods is that the LDMI approach yields perfect decomposition results without an unexplained residual term that potentially hardens result interpretation (Ang, 2005). Moreover, it is consistent in aggregation and can effectively handle zero values. However, a differentiation needs to be made between the multiplicative application of the LMDI scheme and the additive application of the LMDI scheme. The main difference between these two approaches is that the additive LMDI decomposes the absolute difference of a given indicator over time, whereas multiplicative LMDI decomposes the ratio of a given indicator. A mathematical formulation of the two different application methods is provided in Figure 2. Within Figure 2, *V* represents an energy-related aggregate, such as for example greenhouse gas emissions. Moreover, changes to this aggregate over time come from *n* factors, with each factor being associated with a quantifiable variable whereby there are *n* variables ranging from x_1 to x_n (Ang, 2005). Additionally, there may be a sub-category of the aggregate that is to be studied, for example economic sectors. Such a sub-category can be represented by the subscript *i*, which in this case would indicate a given economic sector. While both the multiplicative as well as the additive approach decompose the energy-related aggregate under inspection, the additive formula is decomposing into differences (ΔV_{xn}), whereas the multiplicative formula is decomposing into determinant effects (D_{xn}). The total overall indicator change is indicated by the subscript *tot*.

Figure 2: Additive and multiplicative decomposition formulae

<u>Additive formula</u>: $\Delta V_{tot} = V^T - V^0 = \sum \Delta V_{xn} = \Delta V_{x1} + \Delta V_{x2} + \cdots + \Delta V_{xn}$

with $\Delta V_{xn} = \sum_i \Delta V_{xn,i}$

<u>Multiplicative formula</u>: $D_{tot} = \frac{V^T}{V^0} = \prod D_{xn} = D_{x1} \times D_{x2} \times \ldots \times D_{xn}$

with $D_{xn} = \prod_i D_{xn,i}$

Source: Ang (2005)

Based on the information of Figure 2, the general index decomposition analysis (IDA) identity can be formalized as in equation (1), where at the sub-category level the relationship $V_i = x_{1,i} \times x_{2,i} \times \ldots \times x_{n,i}$ holds. Again, *V* is representing an energy-related indicator, whereas the $x_{n,i}$ values represent the variables associated with each factor that can change the indicator. The subscript *i* denotes a sub-category under inspection, such as economic sectors for instance.

$$(1)\quad V = \sum_i V_i = \sum_i x_{1,i} \times x_{2,i} \times \ldots \times x_{n,i}$$

Based on the general IDA identity in (1), the analysed indicator *V* changes from $V^0 = \sum_i V_i^0 = \sum_i x_{1,i}^0 \times x_{2,i}^0 \times \ldots \times x_{n,i}^0$ in the base year 0 to $V^T = \sum_i V_i^T = \sum_i x_{1,i}^T \times x_{2,i}^T \times \ldots \times x_{n,i}^T$ in the comparison year T. Depending on the aim as well as on the methodology of the analysis, this change can be evaluated using either additive or multiplicative LMDI decomposition (see Figure 2). The general formulae for both approaches, together with the underlying IDA identity, are illustrated in Table 3.

Table 3: LMDI formulae for the general case with *n* factors

IDA identity	$V = \sum_i V_i = \sum_i x_{1,i} \times x_{2,i} \times \ldots \times x_{n,i}$	
Scheme	Multiplicative decomposition: $D_{tot} = \frac{V^T}{V^0} = \prod D_{xn} = D_{x1} \times D_{x2} \times \ldots \times D_{xn}$	Additive decomposition: $\Delta V_{tot} = V^T - V^0 = \sum \Delta V_{xn} = \Delta V_{x1} + \Delta V_{x2} + \cdots + \Delta V_{xn}$
LMDI formulae	$D_{xn} = \exp\left(\sum_i \frac{\frac{(V_i^T - V_i^0)}{(\ln(V_i^T) - \ln(V_i^0))}}{\frac{(V^T - V^0)}{(\ln(V^T) - \ln(V^0))}} \times \ln\left(\frac{x_{n,i}^T}{x_{n,i}^0}\right)\right)$	$\Delta V_{xn} = \sum_i \frac{V_i^T - V_i^T}{\ln(V_i^T) - \ln(V_i^T)} \times \ln\left(\frac{x_{n,i}^T}{x_{n,i}^0}\right)$

Source: Ang (2005)

As can be seen in Table 3, the main difference between the two approaches is that the multiplicative decomposition results in determinants explaining the indicator change in terms of the relative contribution of a given factor (D_{xn}), while the outcome of the additive decomposition is simply the absolute change contributed by a given factor (ΔV_{xn}). Even though the two LMDI application approaches in Table 3 may appear dissimilar, they relate to each other through the additive property of the multiplicative LMDI approach and the general relationship between the multiplicative and additive decomposition. The additive property of the multiplicative approach is shown in (2), while the relationship between the two approaches is formalized in (3).

$$(2)\ \ln(D_{tot}) = \ln(D_{x1}) + \ln(D_{x2}) + \cdots + \ln(D_{xn})$$

$$(3)\ \frac{\Delta V_{tot}}{\ln(D_{tot})} = \frac{\Delta V_{x1}}{\ln(D_{x1})} = \frac{\Delta V_{x2}}{\ln(D_{x2})} = \cdots = \frac{\Delta V_{xn}}{\ln(D_{xn})}$$

The decomposition reversibility due to the multiplicative LDMI results' additive property (shown in (2)) and the simple relationship between the additive and multiplicative decomposition (shown in (3)) makes a separate decomposition between the two schemes unnecessary (Ang, 2005). Another important advantage of the LDMI method that was mentioned before is that it is consistent in aggregation (Ang & Liu, 2001). This property is particularly beneficial for the research within this thesis, as the estimates on a yearly basis can be aggregated to give the corresponding estimates at grouped time ranges (Ang, 2005), which is relevant for the aggregation of the two commitment periods of the Kyoto Protocol. However, there are also certain limitations to this method that need to be anticipated. The LDMI formulae contain multiple logarithmic terms, which means the respective variables cannot have negative values (Ang, 2005). Although the occurrence of negative values in index decomposition analysis (IDA) is rare, their existence does limit the LDMI. A more likely situation that results in the same limitation is the presence of zero values in the data. This problem was solved by replacing all zeros in the data by a small positive constant of 10^{-15}. After deciding on using the multiplicative LMDI approach, the next step of my analysis is to calculate all coefficients that are needed as intermediary inputs for the calculation of the five determinants.

4.3 Coefficient calculation (intermediary inputs)

After allocating the processed input data to the six economic sectors under inspection, I calculate a multitude of coefficients that are needed to proceed with the decomposition analysis. These coefficients include the GVA per capita (U), the value-added shares of each sector (S_i), the energy intensity of each sector (I_i), and the emission intensity of each sector (K_i). Each of these coefficients serves as an intermediary input that is needed for the computation of the determinants in the next step. Additionally, the weight coefficient (w_i) that is needed for the determinant calculation is also being computed in accordance with Ang and Liu (2001). The first of the coefficients, the GVA per capita (U), is calculated by simply dividing the population (P^T) of the respective year T from the overall GVA for the same year (Q^T). Its formal representation is described in (4).

$$(4)\ U^T = \frac{Q^T}{P^T}$$

The next coefficients that need to be calculated for the decomposition of GHG emissions are the value-added shares of each sector (S_i). This ratio indicates the relative contribution of each sector to overall GVA. Consequently, it is calculated by dividing the added value of a given sector at a given time (Q_i^T) by the total GVA at the same time (Q^T). The formal representation of the value-added shares S_i^T can be found below in (5).

$$(5)\ S_i^T = \frac{Q_i^T}{Q^T}$$

The third coefficient calculated from the raw input data is the energy intensity for each sector. Before coming to its formal representation, however, it is important to highlight the difference between the energy intensity coefficient described here and the energy intensity determinant that is part of the final results of my analysis. While the energy intensity calculated here is simply the ratio of consumed energy to GVA (I_i^T), the energy intensity determinant (D_{int}) is a coefficient that indicates the effect of a change in energy intensity on GHG emissions. As such, the energy intensity determinant is part of the decomposition result while the energy intensity here serves as an intermediary input only. This intermediary energy intensity is calculated by dividing the energy use of a given sector for a given year (E_i^T) by the GVA of the same sector in the same year (Q_i^T). The formal representation of this coefficient is provided in equation (6).

$$(6)\ I_i^T = \frac{E_i^T}{Q_i^T}$$

The fourth coefficient needed to proceed with the decomposition analysis is the emission intensity (K_i) for each sector at a given year. Although similar to energy intensity in its name, emission intensity is computed without any GVA data. Instead, it represents the ratio of GHG emissions (C_i^T) to energy use (E_i^T). As such, it is indicating the relationship between energy use and the GHG emissions that go along with it. Again, this coefficient needs to be differentiated from the emission intensity determinant (D_{eint}), which is indicating the effect of a change in emission intensity on GHG emissions. The formal representation of the emission intensity ratio K_i^T is provided below.

$$(7)\ K_i^T = \frac{C_i^T}{E_i^T}$$

Finally, the weight coefficient must be calculated. This weight coefficient is at the root of the decomposition analysis and has been the main object of adjustment and improvements throughout the available decomposition literature. As already touched upon in the theory section, the decomposition analysis within this paper follows the LMDI I approach proposed by Ang and Liu (2001). In contrast to previous weight functions, Ang & Liu's (2001) approach is consistent in aggregation, thus allowing me to aggregate time series data into the two commitment periods of the Kyoto Protocol. In the weight function proposed by Ang and Liu (2001), the logarithmic mean of the factorial value is divided by the logarithmic mean of the aggregate value. The formal representation of the weight function can be found in (8), where the numerator represents the logarithmic mean of the factorial value and the denominator the logarithmic mean of the aggregate value.

$$(8)\ w_i = \frac{\frac{(C_i^T - C_i^0)}{(\ln(C_i^T) - \ln(C_i^0))}}{\frac{(C^T - C^0)}{(\ln(C^T) - \ln(C^0))}}$$

The intermediary inputs for all decomposed time intervals can be found in Appendix C. The weight coefficient is calculated for each sector separately an can be found in Appendix E. Next, after calculating all coefficients that are needed as intermediary inputs, I proceed by finalizing the decomposition analysis and computing the determinants. The determinants represent the final outcomes of my analysis and indicate the effect of each determinant on GHG emission changes. Each of the determinants is calculated using the raw input data and the intermediary input data that was calculated before.

4.4 Determinant Calculation

As shortly touched upon in the theory section, I differentiate between five determinants of GHG emission changes in my application of the LMDI I model. The product of these determinants, also being referred to as *effects* throughout this paper, explains the observed change of emissions between two years. Furthermore, the determinants used to assess emission changes were not chosen randomly, but instead are based upon the Kaya identity (Kaya, 1989) and the IPAT model (Ehrlich & Holdren, 1971). While the original Kaya identity differentiates between four determinants that explain man-made emission changes (Kaya, 1989), the model within this thesis considers five determinants. As such, the LMDI I model within this paper follows the example set by Ang and Liu (2001) and is based on an extended Kaya identity. The four determinants of the initial Kaya identity, which were also adopted for my decomposition analysis, include an energy intensity effect (D_{int}), an emission intensity effect (D_{eint}), a GVA per capita effect (D_{act}), as well as a population effect (D_{pop}) (Kaya, 1989, Kaya & Yokobori, 1997). The fifth determinant added to my analysis is the effect of structural change on emission changes (D_{str}). As was shown in the theory section, there exist multiple other potential determinants that are based on an extended Kaya identity, but for the purpose of my analysis the five determinants discussed before are considered the most fitting. The following paragraphs provide a detailed explanation of each determinant, its formal representation and what it is supposed to capture in the context of my analysis. I first present the four determinants also present in the Kaya identity, and then proceed by discussing the added structural change determinant.

The energy intensity determinant D_{int} indicates to what degree changes in energy intensity have contributed to the emission changes from the base year to the validation year. As changes in energy intensity are typically the result of technological improvements or from switching to different technologies (Cansino et al. 2015), this determinant serves as an indicator for how energy-related technological advancements affect GHG emissions. It is important to note, however, that this effect is capturing only the effect that changes in energy intensity had on emission changes, not what drove the changes in energy intensity itself. The formal representation of this determinant is provided below.

$$(9)\ D_{int} = \exp\left(\sum_i w_i * \ln\left(\frac{I_i^T}{I_i^0}\right)\right) = \exp\left(\sum_i \frac{\frac{(C_i^T - C_i^0)}{(\ln C_i^T - \ln C_i^0)}}{\frac{(C^T - C^0)}{(\ln C^T - \ln C^0)}} * \ln\left(\frac{I_i^T}{I_i^0}\right)\right)$$

The emission intensity determinant D_{eint} on the other hand indicates to what degree changes in emission intensity have contributed to the observed emission changes. As was shown in formula (7), emission intensity is the ratio of CO_2 equivalent GHG emissions to consumed energy at a given period and sector. Hence, a lower emission intensity means that the same amount of consumed energy led to fewer emissions or that the same amounts of emissions was achieved consuming less energy, respectively. This ratio between emissions and consumed energy is mainly dependent on what type of energy sources are consumed, as different energy sources also have different embodied emission content. Brown coal, for example, has a significantly higher embodied emission content than natural gas, as indicated by their respective emission factors (IPCC, 2006). Consequently, emission intensity represents the quality of the energy mix from a GHG mitigation perspective (Cansino et al., 2015). The formal representation of the emission intensity determinant D_{eint} is provided below in equation (10).

$$(10) \qquad D_{eint} = \exp\left(\sum_i w_i * \ln\left(\frac{K_i^T}{K_i^0}\right)\right) = \exp\left(\sum_i \frac{\frac{(C_i^T - C_i^0)}{(\ln C_i^T - \ln C_i^0)}}{\frac{(C^T - C^0)}{(\ln C^T - \ln C^0)}} \ln\left(\frac{K_i^T}{K_i^0}\right)\right)$$

Next, the economic activity determinant D_{act} is explained. This determinant captures to what degree changes in GVA per capita contributed to changes in GHG emissions for the observed time interval. In general, GVA per capita is the ratio of production to population as seen in equation (4). Consequently, changes to this determinant are the result of changes in either GVA or population. For instance, if the economic activity determinant is below one despite a growing GVA per capita, it would indicate a decoupling process of emissions from per capita GVA. As furthermore showcased by Cansino et al. (2015), this effect represents the affluence effect within the traditional IPAT equation. The formal representation of the economic activity determinant D_{act} is provided below.

$$(11) \qquad D_{act} = \exp\left(\sum_i w_i * \ln\left(\frac{U^T}{U^0}\right)\right) = \exp\left(\sum_i \frac{\frac{(C_i^T - C_i^0)}{(\ln C_i^T - \ln C_i^0)}}{\frac{(C^T - C^0)}{(\ln C^T - \ln C^0)}} \ln\left(\frac{U^T}{U^0}\right)\right)$$

The fourth determinant calculated within my decomposition analysis is the population effect D_{pop}. This effect is present both in the original IPAT equation as well as in the regular Kaya identity. As the name might already suggest, this determinant captures to what degree changes in the population of Belgium affect changes in GHG emissions during the observed time interval. As long as the population is growing, this determinant is also expected to grow. If the determinant would be below one despite a growing population, this would indicate a decoupling of emissions from population growth. However, throughout the reviewed literature there was not a single example of a growing population that had a negative effect on emissions. Typically, this determinant is only below one when the population of a country is shrinking. The formal representation of the population determinant D_{pop} is provided below.

$$(12) \qquad \mathrm{D_{pop}} = \exp\left(\sum_i w_i * \ln\left(\frac{P^T}{P^0}\right)\right) = \exp\left(\sum_i \frac{\frac{\left(C_i^T - C_i^0\right)}{\left(\ln C_i^T - \ln C_i^0\right)}}{\frac{\left(C^T - C^0\right)}{\left(\ln C^T - \ln C^0\right)}} \ln\left(\frac{P^T}{P^0}\right)\right)$$

Finally, the structural change determinant D_{str} is indicating to what degree changes in the economy structure of Belgium affect emission changes during the observed time interval. In essence, this determinant is dependent on the composition of economic activities within Belgium. As not all sectors and activities within an economy are equally contributing to GHG emissions, changes in the economic structure of Belgium might have a significant impact on emission changes. If the structural change determinant is below one, this might indicate a transition towards activities with a lower carbon footprint. Likewise, if above one, this determinant might indicate a transition towards more emission-heavy activities such as many manufacturing activities. The formal representation of the structural change determinant D_{str} is provided below.

$$(13) \qquad D_{str} = \exp\left(\sum_i w_i * \ln\left(\frac{S_i^T}{S_i^0}\right)\right) = \exp\left(\sum_i \frac{\frac{\left(C_i^T - C_i^0\right)}{\left(\ln C_i^T - \ln C_i^0\right)}}{\frac{\left(C^T - C^0\right)}{\left(\ln C^T - \ln C^0\right)}} \ln\left(\frac{S_i^T}{S_i^0}\right)\right)$$

Moreover, multiplying all five determinants will result in the total emission effect D_{tot}. As mentioned before, the five determinants explain the observed change in GHG emissions. Consequently, this means that the total emission determinant D_{tot} is equal to the ratio of GHG emissions from the terminal year to the base year. This relationship between determinants and emission changes within the multiplicative LMDI model can be formalized as in equation (14), where D_{tot} represents the product of all five determinants and C^T as well as C^0 represent emissions in the terminal year and base year, respectively.

$$(14) \qquad D_{tot} = \frac{C^T}{C^0} = D_{int} \times D_{eint} \times D_{act} \times D_{str} \times D_{pop}$$

Additionally, the total effect can be calculated by either multiplying all determinants or by multiplying the contributions of all sectors as shown in equation (15). The calculated total effect will be the same for both equations.

$$(15) \qquad D_{tot} = \frac{C^T}{C^0} = Agriculture \times Industry \times Energy \times Services \times Transport \times Residential$$

With the calculation of the different determinants on a time series basis being complete, the next step of my analysis is to aggregate these results into the two commitment periods of the Kyoto Protocol. Based on the research design discussed before, the determinants will first be calculated on a yearly basis for all years between 2008 and 2018. Afterwards, the results of the time series analysis will be aggregated into the two distinct commitment periods of the Kyoto Protocol. Doing so ensures to capture the magnitude of all effects in the commitment periods of the Kyoto Protocol without discarding the in-between years. This means that the relationship between the decomposition on a yearly basis and on an aggregated basis can be described as in equation (16) and (17).

$$(16) \quad D_n^{Kyoto\_1} = D_n^{08-09} \times D_n^{09-10} \times D_n^{10-11} \times D_n^{11-12}$$

$$(17) \quad D_n^{Kyoto\_2} = D_n^{12-13} \times D_n^{13-14} \times D_n^{14-15} \times D_n^{15-16} \times D_n^{16-17} \times D_n^{17-18}$$

In (16), the superscript *Kyoto_1* is indicating the aggregated time period relating to the first commitment period of the Kyoto Protocol. The superscripts *08-09, 09-10, 10-11, 11-12* are indicating the respective years that are part of the first commitment period for which the determinants have been calculated in the step before. The subscript *n* is indicating a given determinant, such as for instance the energy intensity determinant. This means that the energy intensity effect on the aggregated level is the product of all energy intensity determinants reported for the entailed years. The same logic applies to equation (17), which is depicting the aggregated time period relating to the second commitment period. Based on the formulae (1) – (15), the LMDI decomposition for GHG emissions in Belgium can formalized. All LMDI formulae needed for the decomposition of GHG emissions in Belgium are presented in Table 4, together with the underlying IDA identity.

Table 4: LMDI formulae for decomposing GHG emissions in Belgium

IDA identity	$C = \sum_i C_i = \sum_i \frac{Q}{P} \times \frac{Q_i}{Q} \times \frac{E_i}{Q_i} \times \frac{C_i}{E_i} \times P = \sum_i U \times S_i \times I_i \times K_i \times P$
Scheme	Multiplicative decomposition: $D_{tot} = \frac{C^T}{C^0} = \prod D_n = D_{act} \times D_{str} \times D_{int} \times D_{eint} \times D_{pop}$ Weight coefficient: $w_i = \frac{\frac{(C_i^T - C_i^0)}{(\ln(C_i^T) - \ln(C))}}{\frac{(C - C^0)}{(\ln(C^T) - \ln(C))}}$
LMDI formulae	$D_{act} = \exp\left(\sum_i w_i \times \ln\left(\frac{U^T}{U^0}\right)\right)$ $D_{str} = \exp\left(\sum_i w_i \times \ln\left(\frac{S_i{}^T}{S_i{}^0}\right)\right)$ $D_{int} = \exp\left(\sum_i w_i \times \ln\left(\frac{I_i{}^T}{I_i{}^0}\right)\right)$ $D_{eint} = \exp\left(\sum_i w_i \times \ln\left(\frac{K_i{}^T}{K_i{}^0}\right)\right)$ $D_{pop} = \exp\left(\sum_i w_i \times \ln\left(\frac{P^T}{P^0}\right)\right)$

Note: Based on the determinant results obtained on a yearly basis, the aggregate values of the determinants will then be calculated to the commitment periods as described in equation (15) and (16). *Source*: author illustration

In general, if any of the determinants takes on a value of below one, it means that this determinant contributed to a decrease in emissions. Similarly, if above one, the respective determinant contributed to emission increases. When looking at the determinant results, their relative contribution to emission changes can be evaluated based on the difference between the value of the determinant and the value of one. For example, if the energy intensity effect takes on the value $D_{int} = 1.09$, then this means that the energy intensity effect increased emissions by 9 percent. Similarly, if the same determinant has a value of $D_{int} = 0.94$ it means that the changes in energy intensity reduced emissions by 6 percent. After now having discussed the different parts of my methodology and approach on decomposing Belgian GHG emission changes, the next chapter will present the results of the analysis followed by a discussion and interpretation of the obtained results.

5 Emperical Analysis

The empirical analysis section contains multiple chapters that serve different purposes. First, a results chapter will present the results of the decomposition analysis and provide a brief explanation of the results that were obtained. This will be done first for the time series analysis and then for the aggregated commitment periods in a separate sub-chapter. Afterwards, I will critically reflect on the results and put my findings into the context of the research aim as well as previous research. In doing so, I will highlight the differences and similarities that are found when comparing this paper with previous studies. Furthermore, I will discuss the role of my findings for potential policy implementations. When discussing different policy implications, I will lay focus on isolating the determinants and economic sectors that would serve as the most effective levers in regulating GHG emissions.

5.1 Results

After discussing the methodology being used for decomposing GHG emission changes as well as explaining the data being used, I will now proceed by presenting the results of my analysis. As two research questions were stated, the presentation of the results will also be split into two parts, with each part relating to the respective step of my analysis. First, the results of the time series decomposition are presented.

5.1.1 Time Series Decomposition Results

The first step of my analysis was to decompose the GHG emission changes in Belgium for all years between 2008 and 2018. Analysing the emission changes from each year to the next one has the great advantage of providing a clear and detailed picture of the development of determinants and economic sectors over time. This allows to assess the impact of each determinant and economic sector on emission changes over time. Additionally, it may indicate trends that have emerged throughout the observed years. At first, a closer look will be taken on the development of the GHG emission determinants between 2008 and 2018. The results of the decomposition analysis for each determinant are provided in Table 4. Within Table 4, all values have been rounded to only contain four decimals. The reason I did not round them further is that in some cases there are only small differences which would not be visible if there were only one or two decimals.

Table 5: Time Series Decomposition Results for Determinants

	D_{act}	D_{str}	D_{int}	D_{pop}	D_{eint}	D_{tot}
2008-2009	0,9701	0,9545	0,9985	1,0081	0,9674	0,9017
2009-2010	1,0192	1,0442	1,0170	1,0081	0,9728	1,0614
2010-2011	1,0039	0,9842	0,9201	1,0148	1,0117	0,9334
2011-2012	1,0016	0,9692	0,9936	1,0068	0,9936	0,9649
2012-2013	0,9978	0,9712	0,9980	1,0056	1,0014	0,9739
2013-2014	1,0116	1,0192	0,9331	1,0038	1,0150	0,9803
2014-2015	1,0167	1,0564	1,0095	1,0050	0,9571	1,0430
2015-2016	1,0028	0,9681	1,0282	1,0066	0,9868	0,9916
2016-2017	1,0122	0,9801	0,9989	1,0036	1,0007	0,9954
2017-2018	1,0145	0,9409	1,0628	1,0041	0,9791	0,9973

Note*:* For a full presentation of decomposition results, please refer to Appendix D. *Source*: author calculations

In general, the table above differentiates between the five determinants as well as the total effect of these determinants on greenhouse gas emissions. For the first period from 2008 to 2009, GHG emissions decreased by roughly 10 percent, indicated by the total effect of $D_{tot} \approx 0{,}90$. Having a closer look at the five determinants, it can be observed that the structural change effect contributed most to this decrease in emissions ($D_{str} \approx 0{,}95$), whereas the population effect positively contributed to emissions ($D_{pop} \approx 1{,}008$). The other determinants also contributed to the emission decrease during that period, although not as much as the structural change determinant. Interestingly, the next period from 2009 to 2010 exhibits increasing GHG emissions of around 6 percent in Belgium ($D_{tot} \approx 1{,}06$). During that period, it appears that this increase in emissions was mostly driven by the economic activity determinant ($D_{act} \approx 1{,}019$) and the structural change determinant ($D_{str} \approx 1{,}044$). Furthermore, the energy intensity effect as well as the population effect also positively contributed to this increase in GHG emissions. The only effect that counteracted the positive contribution of the previous four determinants was the emission intensity effect, which had a negative impact on GHG emissions in the period from 2009-2010 ($D_{eint} \approx 0{,}97$). For the period between 2010 and 2011, GHG emissions have decreased by roughly 7 percent ($D_{tot} \approx 0{,}93$). Notably, out of the five determinants, only two contributed to this negative emission development, whereas three determinants had a positive impact on emissions. The economic activity effect, as well as the population effect and emission intensity effect all led to an increase in emissions. However, their positive contribution was offset by the strong negative impact on emissions by the energy intensity effect ($D_{int} \approx 0{,}92$) and the structural change effect ($D_{str} \approx 0{,}98$).

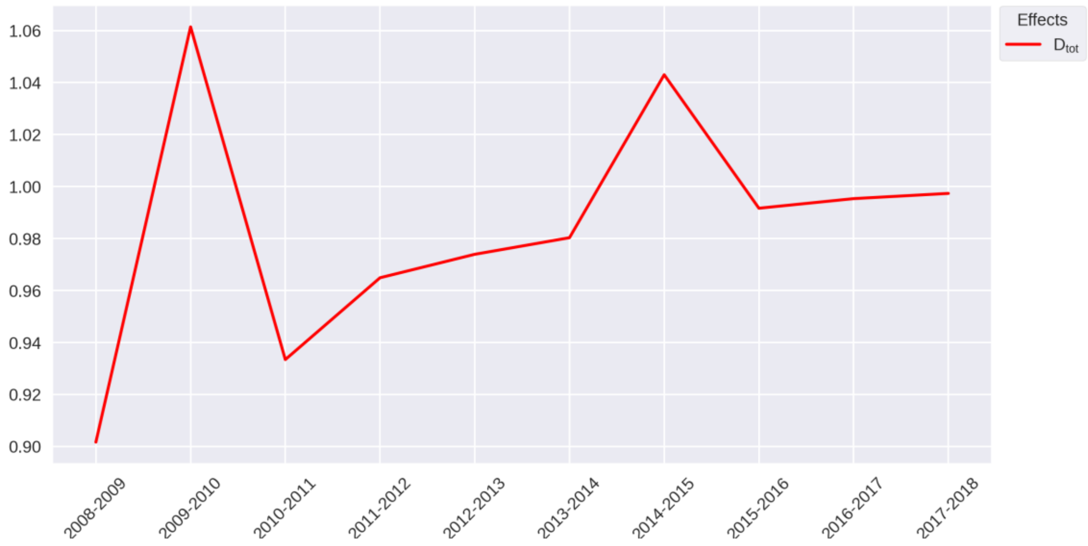
From 2011 to 2012, a decrease in emission of around 4 percent can be observed ($D_{tot} \approx 0{,}96$). This reduction was mainly driven by structural changes ($D_{str} \approx 0{,}97$), although energy intensity and emission intensity also slightly contributed to this reduction with around 1 percent each. The economic activity determinant as well as the population determinant on the other hand positively contributed to GHG emissions, but only to a rather small degree ($D_{act} \approx 1{,}002$ and $D_{pop} \approx 1{,}007$). For the period from 2012 to 2013, GHG emissions decreased by around 3 percent ($D_{tot} \approx 0{,}97$). This reduction was again mainly driven by the structural change determinant (D_{str}

≈ 0,97). Contrary to the period from 2011 to 2012, however, the economic activity determinant also negatively contributed to this development (D_{act} ≈ 0,99), whereas the emission intensity determinant slightly increased GHG emissions (D_{eint} ≈ 1,001). Nevertheless, the changes in determinants from the period of 2011-2012 to 2012-2013 were only marginal and in general the two periods exhibit a very similar pattern of determinant contributions. The next period is the one from 2013 to 2014. During this time, a reduction of GHG emission of around 2 period can be observed (D_{tot} ≈ 0,98). This decrease was driven solely by changes in energy intensity (D_{int} ≈ 0,93), as in fact all other determinants positively contributed to GHG emissions. Of the other four determinants, the structural change effect was the one contributing most to an increase in emissions (D_{str} ≈ 1,019). Contrary to the last three time periods, the period from 2014-2015 was marked by a relatively strong increase in GHG emissions (D_{tot} ≈ 1,043). This increase was mainly driven by the structural change effect (D_{str} ≈ 1,056), as well as by contributions from the economic activity determinant (D_{act} ≈ 1,017), the energy intensity determinant (D_{int} ≈ 1,009), and the population determinant (D_{pop} ≈ 1,005). The emission intensity determinant was the only one negatively contributing to emission changes (D_{eint} ≈ 0,96), however, not enough to offset to positive contributions of the other four effects.

During the period from 2015-2016, emissions then slightly decreased again by almost 1 percent (D_{tot} ≈ 0,99). This decrease was the result of structural changes (D_{str} ≈ 0,97) as well as of changes in emission intensity (D_{eint} ≈ 0,99). The other three determinants were instead positively contributing to emission changes, with energy intensity being the strongest contributor (D_{int} ≈ 1,03). The time period between 2016 and 2017 also exhibits a decreasing amount of GHG emissions, but only by around 0,5 percent (D_{tot} ≈ 0,995). The structural change determinant (D_{str} ≈ 0,98) as well as the energy intensity determinant (D_{int} ≈ 0,999) contributed to this reduction, whereas the other three determinants positively contributed to GHG emissions. Lastly, the time period from 2017 to 2018 again exhibits a small reduction of greenhouse gas emissions of around 0,3 percent (D_{tot} ≈ 0,997). This reduction was driven by structural change (D_{str} ≈ 0,94) as well as by changes in emission intensity (D_{eint} ≈ 0,98). The remaining three determinants instead positively contributed to emission changes, with the economic activity determinant being the strongest driver of emissions (D_{act} ≈ 1,014).

Interestingly, it should be noted that throughout the periods between 2010 and 2014, the reduction of GHG emissions has steadily decreased. While decreasing by almost 7 percent between 2010 and 2011, emissions decreased by less than 2 percent in the period from 2013 to 2014. Afterwards, emissions appear to be reduced at even smaller margins and in some periods even increase again (for example from 2014 to 2015). However, intuitively presenting the results in form of a table is hard to do. Hence, for a more intuitive representation of the decomposition results, Figures 3 and 4 represent the decomposition results as a time series line plot. Figure 3 showcases the development of the total effect over time, whereas Figure 4 indicates the development of the remaining five determinants. In Figures 3 and 4, the time periods are shown on the x-axis whereas the determinant value is shown on the y-axis.

Figure 3: Time Series decomposition - Total Effect

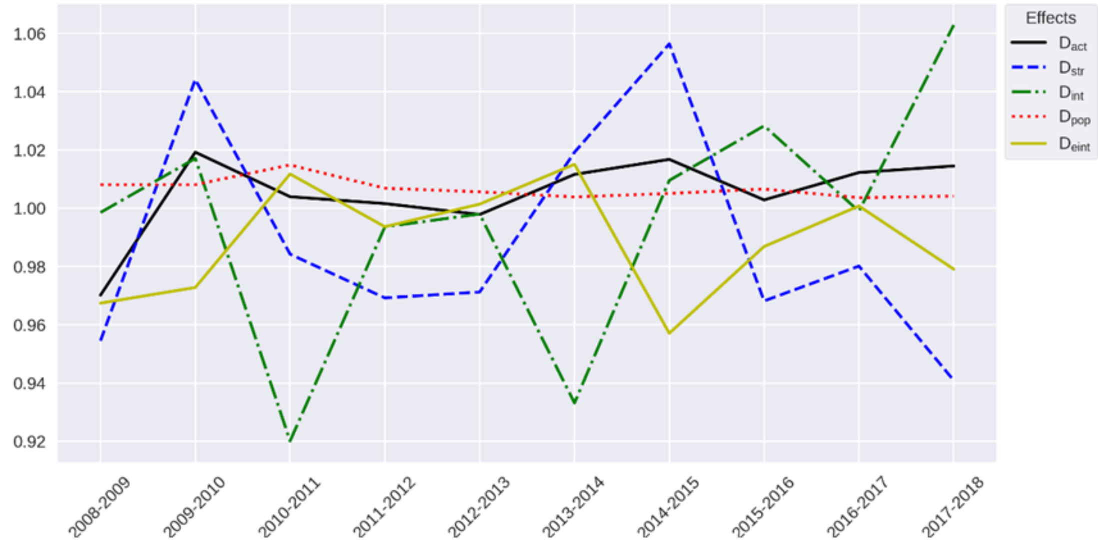


Source: author illustration

In general, Figure 3 is indicating the development of the total effect over time. However, as the total effect equals the ratio of emissions from one year to the next (see equation (14)), Figure 3 is essentially portraying the GHG emission development over time. Whenever the value of the total effect is above one, then emissions were increased during that time. When it is below one, emissions decreased. Looking at Figure 3, a few interesting developments can be observed. First, there is a large difference in the total effect from the period 2008-2009 to 2009-2010. In the period from 2010-2011, the total effect is again significantly different from the previous period. Presumably, this behaviour can be traced back to the global financial crisis that also hit Belgium at the time. This assumption will be further discussed in the discussion chapter. Secondly, it seems like the total effect exhibits a rising trend throughout the last periods observed, indicating that the reduction rate of GHG emissions sunk over time. The reason for this behaviour is most likely linked to the fact that Belgium exceeded its 7.5 percent goal of the first commitment period quite early and by a large margin (see Belgium, 2021), and hence did not feel political pressure to maintain this strong reduction in later periods. This possibility will also be discussed in more detail within the discussion chapter of this paper.

The total effect, however, only portraits the change of emissions from one year to another without explaining what drove this change. For a better intuition of the driving determinants that led to the development of the total effect in Figure 3, a line plot of the developments of the five driving determinants is provided in Figure 4. Again, time periods are shown on the x-axis and determinant values are shown on the y-axis.

Figure 4: Time Series decomposition - Determinants



Source: author illustration

Looking at above illustration, a few interesting trends can be observed. First, looking at the line for the population determinant (D_{pop}), it appears that it is consistently hovering slightly above 1.00 throughout the different time periods. This result is unsurprising, as an increase in population is usually also connected to a rise in emissions (see for example Cansino et al., 2015). If the population determinant would drop below one despite a growing population, this would indicate a decoupling of population from emissions and that more people lead to less emissions. The economic activity effect (D_{act}), although being significantly below one in the first period, also remains slightly above one for most observed time periods. This means that changes in per capita GVA are typically also connected to a slight but constant rise in emissions. The significantly lower value of the economic activity determinant in the period from 2008-2009 is most likely related to the global financial crisis, which would also explain the strong surge in the following period from 2009-2010, when the economy recovered from the financial shock.

Next, a closer look is taken on the determinants of structural change (D_{str}) and energy intensity (D_{int}). While the two lines behave somewhat similar for the time periods between 2008 and 2011, it appears that from 2011 onwards they move counter directional. Especially for the last period from 2017 to 2018, the structural change determinant significantly reduced emissions, whereas the energy intensity determinant appears to be the main driver of increasing emissions. In general, it might be concluded that an upwards trend of energy intensity can be observed from 2013 onwards, whereas the structural change determinant exhibits more of a downwards trend from 2014 onwards. However, it should be kept it mind that with only ten years being analysed, the observed time period within this thesis is rather short and as such not sufficient in showcasing long-term trends. Lastly, the emission intensity (D_{eint}) determinant does not appear to show a consistent pattern throughout time periods, although it is negatively contributing to emissions for most periods. After discussing the development of determinants throughout time, I will now continue by discussing the impact of the different economic sectors within the observed periods to evaluate which sectors were of most importance in reducing or increasing GHG emissions. The decomposition results for each economic sector throughout the observed time periods is provided in Table 6. Again, all values in Table 6 have been rounded to four decimal points.

Table 6: Time Series Decomposition Results for Economic Sectors

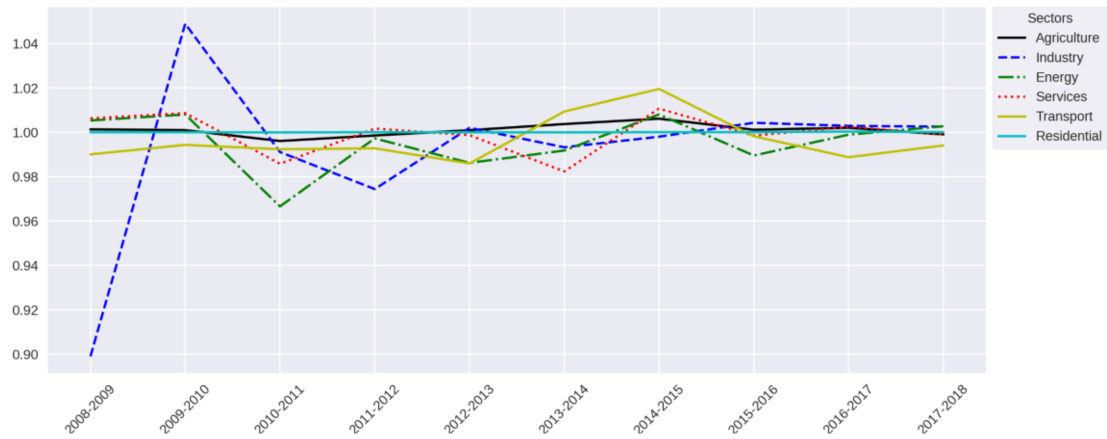
	Agriculture	Industry	Energy	Services	Transport	Residential
2008-2009	1,0013	0,8990	1,0053	1,0063	0,9901	1,0000
2009-2010	1,0009	1,0489	1,0080	1,0086	0,9943	1,0000
2010-2011	0,9961	0,9911	0,9666	0,9858	0,9924	0,9999
2011-2012	0,9985	0,9744	0,9972	1,0017	0,9927	1,0000
2012-2013	1,0009	1,0020	0,9862	0,9987	0,9859	0,9999
2013-2014	1,0037	0,9932	0,9918	0,9823	1,0093	0,9999
2014-2015	1,0061	0,9980	1,0080	1,0106	1,0195	1,0000
2015-2016	1,0011	1,0043	0,9895	0,9985	0,9982	1,0000
2016-2017	1,0020	1,0029	0,9989	1,0025	0,9888	1,0003
2017-2018	0,99904	1,0025	1,0027	0,9990	0,9940	1,0000

Note*:* For a full presentation of decomposition results, please refer to Appendix D. *Source*: author calculations

Looking at Table 6, the contribution of each economic sector on GHG emission changes is showcased. One important aspect to note is that the total effect on GHG emissions is not provided in above table. The reason for this is that, as mentioned before, the product of all sector effects within a given time period equals the total effect of the same period shown in Table 5. That means that the product of all determinant effects is the same as the product of all sector effects (see equation (15)). As such, I will discuss the sector effects not from one period to the next, but rather discuss their development throughout periods and highlight certain periods that stand out. First, looking at the Agriculture sector, it can be seen that the values for all time periods are somewhat close to the value of one, where in some periods the Agriculture sector increased emissions and in others it decreased emissions. However, its negative contribution to emissions is never exceeding 0,4 percent (in the period from 2010-2011), while its contribution to increasing emissions is 0,6 percent at most (in the period from 2014-2015). In general, the Agriculture sector does not appear to have a great impact on reducing emissions, nor in increasing them. The Industry sector, on the contrary, appears to have more of an impact on GHG emissions. In the period from 2008-2009, it contributed a little more than 10 percent to the overall reduction in GHG emissions (Industry ≈ 0,89). Afterwards, the Industry sector in some periods continues to reduce emissions, whereas in other periods it increased emissions. In the period from 2009-2010, for instance, it increased emissions by almost 0,5 percent (Industry ≈ 1,048). Between 2011-2012, the Industry sector again decreased emissions by a rather high amount of around 3 percent (Industry ≈ 0,97). Although the Industry sector also contributed to emission reductions and increases in other periods, its impact was not as significant as in the three time periods just discussed. Next, a closer look is taken on the Energy sector. While also being ambiguous in its contribution to GHG emissions, the time period from 2010-2011 is marked by its strongest contribution to emission decrease of around 3.4 percent (Energy ≈ 0,96). In the periods from 2012-2013 and from 2015-2016, the Energy sector reduced emissions by around 1,4 percent (Energy ≈ 0,986) and 1,1 percent (Energy ≈ 0,989), respectively. Interestingly, it does not appear that the Energy sector significantly contributed to emission increases in any of the observed time periods, with the highest contribution to emission increase being only 0,8 percent in the period from 2014-2015 (Energy ≈ 1,008). The Services sector, similar to most other sectors, is ambiguous in its contribution to GHG emissions throughout time. In fact, the Services sector increased emissions in exactly as many time periods as in which it decreased them. However, the overall impact the Services sector had on emissions was rather low in general, with the strongest negative impact from 2010 to 2011 (Services ≈ 0,98) and the strongest positive impact in the period from 2014 to 2015 (Services ≈ 1,01).

The Transport sector contributed mostly negatively to GHG emissions changes, with exception for the periods from 2013 to 2014 and from 2014 to 2015. The strongest positive contribution to GHG emissions was in the period from 2014 to 2015, where the Transport sector contributed almost 2 percent (Transport ≈ 1,02) to emission increases. In all other periods, the Transport sector negatively contributed to GHG emissions, with the strongest negative contribution being 1.5 percent in the period from 2012 to 2013 (Transport ≈ 0,985). Lastly, the Residential sector is marked by a remarkably little impact on GHG emissions throughout time. While in general being very close to the value of one, the impact of the Residential sector also differs based on the period under observation. However, the impact of the Residential sector in either direction never exceeded 0.0006 percent, which was the case in the period from 2010 – 2011 (see Appendix D). As such, its contribution to GHG emission changes can be considered marginal. For a better visualization of the development of economic sectors throughout time, Figure 4 provides a line plot of the sectoral development throughout periods.

Figure 5: Time Series decomposition – Sectors



Source: author illustration

In above Figure, the x-axis is indicating the different time periods and the y-axis is showing the determinant values. The first thing that becomes apparent when looking at Figure 5 is that the different sectors become less impactful over time. Especially the Industry sector as well as the Energy sector stand out, as their impact appears to be shrinking the most over time. In general, the results portrayed in Figure 4 suggest that the impact of sectors on GHG emissions becomes less relevant over time. Notably, such a development was not observed for the five determinants (see Figure 4). If the impact of the sectors falls over time while the impact of the determinants is remaining more or less constant (independent of whether or not this impact is negative or positive), then this would mean that the determinants become relatively more important in driving GHG emissions. This has important implications for policies trying to tackle GHG emissions in the most effective way, which will be further discussed in the policy implications chapter. However, before coming to the policy implications, the results of the aggregated decomposition will be presented first.

5.1.2 Aggregated Decomposition Results

The second step of my analysis was the aggregation of years into two commitment periods relating to the ones established in the Kyoto Protocol and the Doha amendment, respectively. As shortly touched upon in the methodology section, one of the advantages of using the multiplicative LMDI approach is that the results can be aggregated easily and consistently. This means that the values for each determinant on the aggregated level are the product of the values for the same determinant of all years entailed in the respective commitment period (see equations (16) and (17)). The decomposition results for the first commitment period are reported in Table 7.

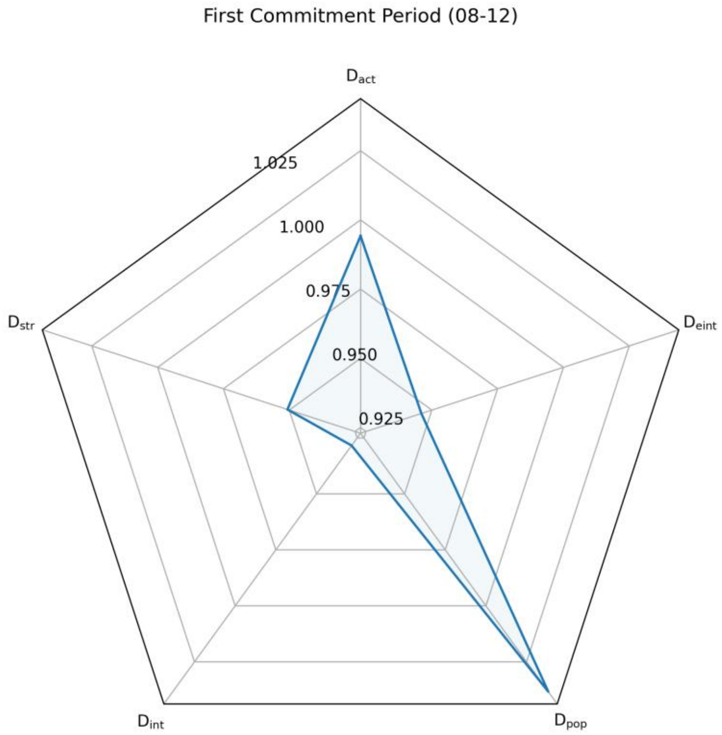
Table 7: Determinant Decomposition Results First Commitment Period (08-12)

	D_{act}	D_{str}	D_{int}	D_{pop}	D_{eint}	D_{tot}
First Commitment Period	0,9942	0,9507	0,9284	1,0383	0,9460	0,8620

Source: author calculations

Looking at above table reveals interesting insights. First, it appears that during the first commitment period of the Kyoto Protocol, the population effect was the only determinant contributing to an increase in GHG emissions of around 4 percent ($D_{pop} \approx 1,04$). All other determinants contributed to a decrease in GHG emissions. In terms of parts of the total effect, the energy intensity effect contributed the strongest to the overall reduction of GHG emissions ($D_{int} \approx 0,93$). The structural change effect as well as the emission intensity effect contributed to this decrease with $D_{str} \approx 0,95$ and $D_{eint} \approx 0,95$, respectively. The economic activity effect only had a small negative effect on GHG emissions of around 1 percent ($D_{act} \approx 0{,}99$). Overall, the total effect of $D_{tot} \approx 0{,}86$ suggests that in the first commitment period of the Kyoto Protocol, Belgium reduced its emissions by almost 14 percent. This result is exactly in line with the GHG emission reductions that were reported in the *2021 National Inventory Report* of greenhouse gases in Belgium (Belgium, 2021). However, in contrast to the *2021 National Inventory Report*, the decomposition analysis carried out within this paper allows to evaluate what determinants drove this reduction of GHG emissions. Figure 6 illustrates the determinant contributions to emission changes in form of a radar chart for a more intuitive understanding of what determinants drove this emission reduction in Belgium during the first commitment period of the Kyoto Protocol. In general, if the value for a given determinant is close to the centre of the radar chart, then it had a decreasing effect on emissions. If the value lies more on the outer lines above 1.000, then the determinant increased emissions.

Figure 6: Radar Chart of Emission Determinants (2008-2012)



Source: author illustration

Above illustration allows to put the values reported in Table 7 in a graphical context. Here, it can be clearly seen that the population effect was the only determinant significantly above the value of one and hence increasing emissions. While all other determinants contributed to the emission reduction, the population determinant increased emissions, however, not enough no offset to strong negative effect on emissions of the other determinants. It can also be clearly seen that the energy intensity effect contributed the most to the overall reduction in GHG emissions during the first commitment period, as it is closest to the centre of the chart. After having inspected the contribution of determinants to emission changes during the first commitment period, the contribution of each economic sector is now presented. The decompostition results for each economic sector during the first commitment period are reported in Table 8.

Table 8: Sector Decomposition Results First Commitment Period (08-12)

	Agriculture	Industry	Energy	Services	Transport	Residential
First commitment period	0,9969	0,9107	0,9768	1,0022	0,9698	1,0000

Source: author calculations

Looking at the decomposition results for the economic sectors during the first commitment period reveals interesting information as to what parts of the Belgian economy were of most relevance for the emission reduction observed. Most clearly, the Industry sector contributed to emission reductions by around 9 percent (Industry ≈ 0,91). The Energy sector and the Transport sector were furthermore also important contributors to the overall decrease in GHG emissions, with around 2.4 percent (Energy ≈ 0,976) and 3 percent (Transport ≈ 0,97), respectively. Interestingly, the Services sector appears to have contributed to an increase of emissions instead (Services ≈ 1,002). The reason for this increase is most likely an emission facilitating form of structural change and the migration of workforce across economic sectors. The underlying reasons for the observed changes are further discussed in the next chapter. Lastly, while the Agriculture sector appears to have made a small negative contribution to GHG emissions (Agriculture ≈ 0,99), the Residential sector appears to not have much of an impact on emission changes at all (Residential ≈ 1,00).

After inspecting the decomposition results for the first commitment period, it is now time to discuss the decompostition results of the second commitment period. In accordance with the second research question, the results will be presented in a way that highlights the similarities and differences between the two commitment periods. The determinant decomposition results for the second commitment period are reported in Table 9.

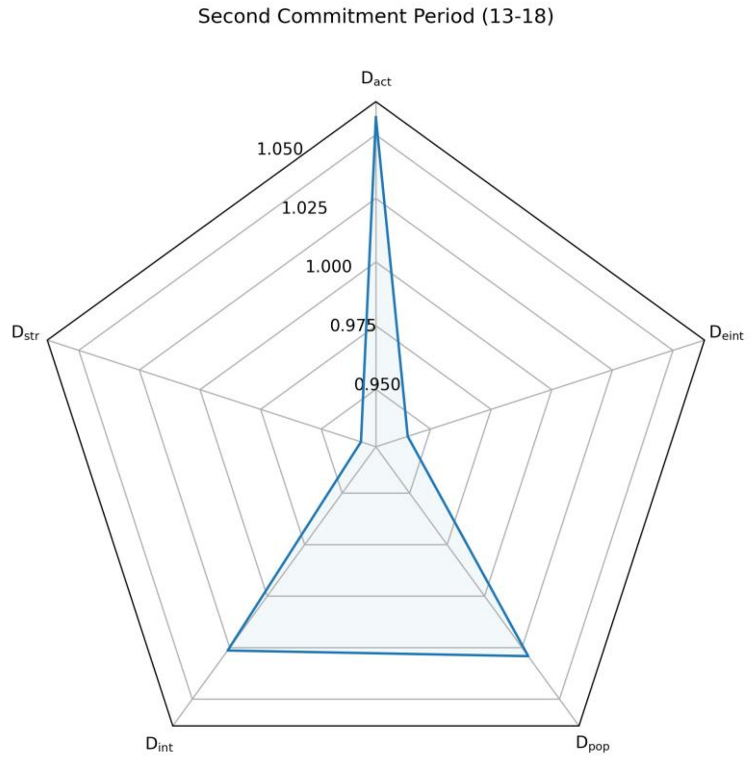
Table 9: Determinant Decomposition Results Second Commitment Period (13-18)

	D_{act}	D_{str}	D_{int}	D_{pop}	D_{eint}	D_{tot}
Second Commitment Period	1,0568	0,9336	1,0264	1,0291	0,9406	0,9803

Source: author calculations

When looking at above table, the first thing that becomes obvious is that the reduction of GHG emissions has been significantly less in the second commitment period than in the first commitment period (see Table 7 & 9). In fact, Belgium has decreased its GHG emissions by around 2 percent only in the second commitment period ($D_{tot} \approx 0,98$) compared to almost 14 percent in the first commitment period. While still being a reduction of emissions, it is interesting to see that the amount of GHG emissions that was reduced shrank by almost 12 percentage points compared to the first commitment period (see Table 7). While it was only one determinant contributing to emission increases during the first commitment period, there are now three determinants that contributed to an increase in emissions in the second commitment period. These determinants include the economic activity effect ($D_{act} \approx 1,06$), the energy intensity effect ($D_{int} \approx 1,03$), as well as the population effect ($D_{pop} \approx 1,03$). Fortunately, the negative contributions of the structural change effect ($D_{str} \approx 0,93$) and the emission intensity effect ($D_{eint} \approx 0,94$) were sufficient to offset the positive contribution of the remaining three determinants. Again, a radar chart is presented to highlight the differences between the different determinants and to showcase the contribution of each determinant to GHG emission changes.

Figure 7: Radar Chart of Emission Determinants (2013-2018)



Source: author illustration

Looking at Figure 7, the differences between the first and second commitment period become apparent. While the only spike during the first commitment period was found in the corner of the population effect, it can now clearly be seen that in the second commitment period three determinants increased GHG emissions. The economic activity effect as well as the energy intensity effect are of particular relevance here. While being negative contributors to GHG emission during the first period (see Figure 6), they are positive contributors to GHG emissions in the second commitment period. Again, this development may reflect the fact that Belgium had exceeded its emissions reduction goals in the first commitment period, and thus did not have political pressure to continue reducing emissions at the same rate. The discussion chapter will discuss this aspect in further detail. Having presented the results of the determinant decomposition, a closer look is now taken on the sectoral contribution to GHG emissions in the second commitment period to evaluate what differences exist when comparing the different economic sectors. The sectoral decomposition results of the second commitment period are reported in Table 10.

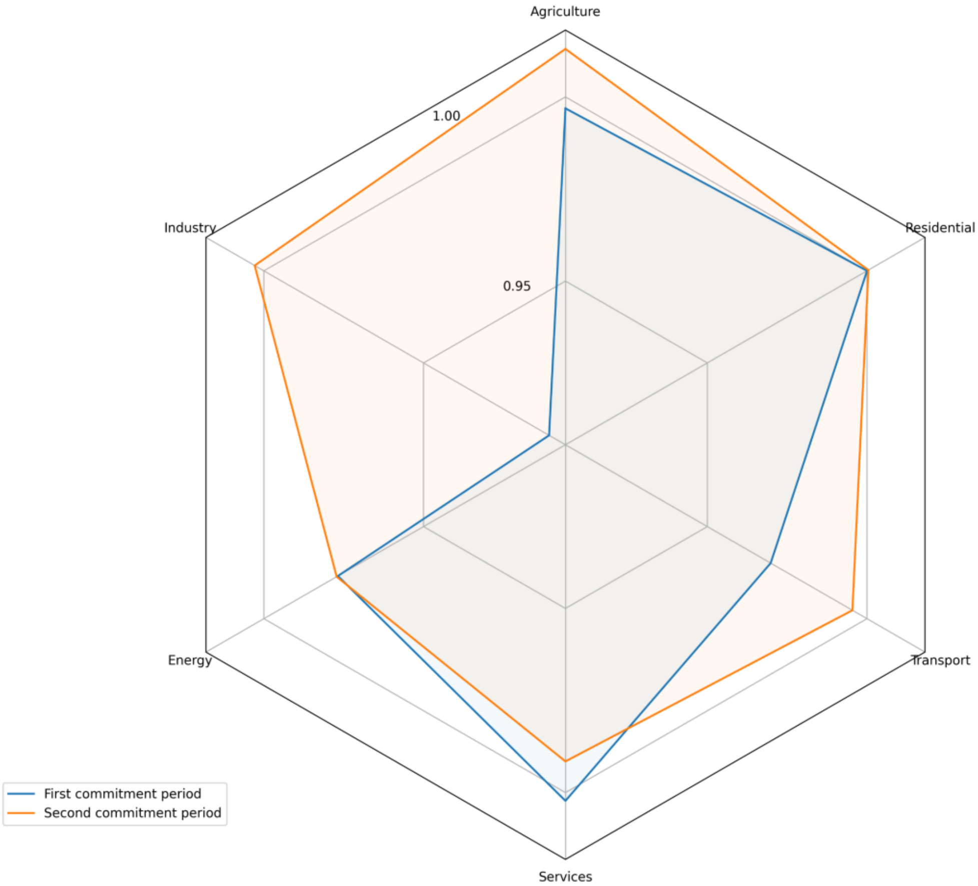
Table 10: Sector Decomposition Results Second Commitment Period (13-18)

	Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**
Second commitment period	1,0130	1,0029	0,9772	0,9915	0,9954	1,0004

Source: author calculations

At first glance, the values reported for the second commitment period do not appear to be significantly different from the ones of the first commitment period (see Table 8). However, some differences do exist. First, the strong negative contribution of the Industry sector in the first commitment period is now in the second commitment period reversed, as the Industry sector is contributing to increasing emissions by 0.2 percent (Industry ≈ 1,002). The impact of the Agriculture sector has furthermore also reversed, now contributing to increasing emissions by roughly 1 percent (Agriculture ≈ 1,013). The contribution of the Energy sector, on the other hand, remains more or less the same when compared to the first commitment period (Energy ≈ 0,98). The Services sector is negatively contributing to GHG emissions in the second period by almost 1 percent (Services ≈ 0,99), whereas it contributed positively during the first commitment period. The Transport sector is still negatively contributing to emission in the second commitment period (Industry ≈ 0,99), although not as much as it has during the first commitment period. Lastly, the Residential sector remains largely unchanged, with it still being of little relevance to the overall change in GHG emissions (Residential ≈ 1,00). For a better visualization of the differences in sectoral contribution to GHG emissions, a combined radar chart showcasing the contribution of sectors during the two commitment periods is provided in Figure 8.

Figure 8: Sectoral Contribution to GHG emissions during commitment periods



Source: author illustration

Looking at above figure, the differences between the two commitment periods in the sectoral contribution are clearly visible. The impacts of the Residential and Energy sector are almost identical for the two commitment periods, whereas especially the Industry sector appears to have undergone substantial changes. The comparatively small changes to the Transport, Services, and Agriculture sector are also made obvious. This may indicate that the Industry sector is the most important sector of the economy when trying to affect emissions from a policy point of view. This result would be in line with Henriques and Kander (2010), who emphasize the relatively high importance of industry and manufacturing for reducing environmental impacts. The surface covered by each of the two graphs furthermore represent the total reduction or increase in emissions. The smaller surface area of the first commitment period indicates a greater reduction of GHG emissions compared to the second commitment period. Within the next chapter, the results will be discussed in relation to the research aim and previous research. Furthermore, the findings of this analysis will be put into context with regards to their policy implications.

5.2 Discussion

Starting with the economic activity determinant it was found that changes in GVA per capita increased GHG emissions for almost all periods, with the only exceptions being the periods from 2008-2009 and the one from 2012-2013. This indicates that for most periods, a growing per capita GVA in Belgium contributed to an increase in emissions. These results are in line with previous decomposition analyses for Belgium, which also find changes in the per capita production to increase emissions (Albrecht et al., 2002; Fernández González et al., 2014). Interestingly, the study by Albrecht et al. (2002) focused on the time period between 1960 and 1996, whereas the observed time span of Fernández González et al. (2014) stretches from 2001 to 2010. Together with this study, which observes the time period from 2008-2018, almost sixty years of emission developments in Belgium are analysed. The fact that increases in production per capita effects contributed to an increase in emissions for most years in all these studies indicates a long-term trend of emissions being increased by increases in per capita production. Given that the periods from 2008-2009 and 2012-2013 are the only periods within this study with a negative contribution of the economic activity determinant, a closer look needs to be taken at these periods. The period from 2008-2009 in this study was the only period under observation where total GVA reduced (see Appendix B), which is likely to have happened due to the global financial crisis of 2008 that had significant impacts on the Belgian economy (De Bruycker & Walgrave, 2013). A similar negative contribution of the economic activity determinant due to the global financial crisis has been pointed out by Cansino et al. (2015) for Spain. The period from 2012-2013, on the other hand, is the only observed time period where the economic activity determinant contributed to decreasing emissions despite Belgium growing in terms of GVA (see Appendix B & C). However, looking at GVA per capita for the respective periods (see Appendix C), it can be seen that the periods from 2008-2009 and 2012-2013 are the only periods with a decreasing GVA per capita from one year to the next. This means that the negative contribution of the economic activity determinant can be explained by the decrease in GVA per capita and no decoupling of emissions from per capita GVA growth can be inferred.

Furthermore, the decomposition of GHG emissions showed that two of the strongest drivers of emission changes in Belgium, both positive and negative, were the energy intensity determinant as well as the emission intensity determinant (see Table 5 and Figure 4). However, their overall impact on emissions was ambiguous and changed depending on the observed time period. After aggregating the time series results into the two commitment periods relating to the Kyoto Protocol, it became clearer what drove emission changes during these two distinct periods. During the first commitment period, the strongest reduction in GHG emissions came from the energy intensity determinant and the emission intensity determinant. During the second commitment period the emission intensity determinant maintained its negative impact on emissions, whereas the energy intensity determinant started positively contributing to emissions (see Table 9). These results relate strongly to the ones obtained in Albrecht et al. (2002), who observed emission changes in Belgium from 1960 to 1996. For the emission intensity determinant, Albrecht et al. (2002) found similar results in the negative contribution to emissions in Belgium. The energy intensity determinant, moreover, is also ambiguous in its impact on emissions in Albrecht et al. (2002). According to Fernández González et al. (2014), the strongest contribution to reducing emissions in Belgium from 2001 to 2010 came from the energy intensity and fuel mix determinant, which is line with the results obtained for the first commitment period in this paper. As mentioned in the theory section, the fuel mix determinant indicates the quality of the energy mix similar to the emission intensity determinant within this paper (Cansino et al., 2015). This means that energy intensity and a switch to cleaner energy sources had the strongest impact on emissions in Belgium from 2001 to 2010 according to Fernández González et al. (2014). Again, the results obtained in this thesis confirm that energy intensity and reduced emission intensity, fostered by a switch to cleaner energy sources, led to the most emissions reductions in Belgium from 2008 to 2012.

Next, the structural change determinant is discussed. Within this thesis it was shown that structural change is ambiguous in its impact between 2008 and 2018, although its impact on emissions was strongly negative for both commitment periods (see Table 7 & 9). Unfortunately, none of the papers regarding decomposition analysis in Belgium analyse a structural change determinant. However, multiple other studies such as the ones by Liu et al. (2007), Cansino et al. (2015), or Zhang et al. (2017) have examined the impact of structural changes and thus allow for a comparison with the results obtained in this thesis. Interestingly, all of the abovementioned studies concluded that the impact of structural change on emissions varies significantly and that no clear trend can be observed. As the results in Figure 4 suggest, a similar ambiguous behaviour of the structural change determinant can be observed for Belgium. Given that the other studies examining a structural effect have a focus on countries such as Spain (Cansino et al., 2015) or China (Liu et al., 2007; Zhang et al., 2017), the results indicate that the ambiguity of the structural change effect is not only characteristic for Belgium. Instead, it seems as if no clear trend of the effect of structural change on emissions can be observed throughout time for multiple countries. Notably, the results obtained for the two commitment periods suggest a strong negative contribution of the structural change determinant for both commitment periods (Table 7 & 9). If only the commitment periods were observed without considering all in-between years, one might wrongfully conclude that structural change consistently decreases emissions, when in fact its impact is quite ambiguous. As such, the two-step methodology chosen for the analysis within this paper has proven to be successful, as the in-between years were not discarded and show the actual pattern of the structural change determinant.

The role of population as a driving force of emissions has been widely discussed in emission research, as it is a part of the IPAT model by Ehrlich and Holdren (1971) as well as of the Kaya identity (Kaya, 1989; Kaya & Yokobori (1997). Similar to many other studies, the results of my thesis also indicate a consistent positive contribution of population to increases in GHG emissions. Such a positive contribution of population growth on emissions is in line with previous findings and suggests a consistent impact of population changes on emissions (Moutinho et al., 2015; Liu et al., 2007). As the population determinant is solely dependent on changes in the population of Belgium, the consistency of its impact on emissions reflects a fairly steady growth rate of the Belgian population, confirmed by the population data obtained from Eurostat (see also Appendix E). As shortly touched upon before, a negative value of the population determinant despite a growing population would indicate a decoupling of emissions from population. Given that no other study that was reviewed for this thesis showed a negative contribution of population growth on emissions, the results of the population determinant are as expected.

Looking at the decomposition results for each economic sector furthermore reveals interesting insights as to what parts of the economy drove emission changes. Having a closer look at Figure 5, it appears as if the importance of each economic sector on GHG emissions in Belgium has decreased over time. While having a strong impact in the first period, regardless of the impact being negative or positive, the overall effect of economic sectors on emissions has decreased. Particularly the Industry sector appears to have become less impactful in terms of its contribution to GHG emissions. This finding is in line with previous findings by Marrero & Ramos-Real (2013), who find that the Industry sector develops less of an impact on emissions throughout time[12]. The Services sector, however, is found to have increased in importance for emissions in the paper of Marrero & Ramos-Real (2013). Contrary to their paper, which is analysing sectors on a European basis, the findings for Belgium suggest that the Service sector also lost in importance and is increasingly aligned to the value of one, hence not having much of an impact on GHG emissions (see Figure 5). In fact, the only sector that appears to maintain its impact on emissions is the Transport sector. It was found that the impact of the Transport sector on emissions was not the strongest to begin with, but it maintained its relevance for emissions in contrast to most other sectors. This development suggests that the Transport sector might be becoming relatively more important than other sectors in the future in terms of its GHG mitigation potential. These findings are in line with studies such as by Andreoni and Galmarini (2012), who argue that the Transport sector has a strong impact potential for emissions.

The Agriculture and Residential sector, on the other hand, were found to have the smallest impact on emission changes in Belgium. It was shown that their impact on emissions was very low to begin with and continued its marginal impact throughout al observed time periods. Although the Agriculture and Residential sector do not appear to have much of an impact on emission changes in Belgium between 2008 and 2018, there are multiple studies stressing the importance of these sectors for climate change and global warming in other regions and countries (see e.g. Robaina-Alves & Moutinho, 2014; Nejat et al., 2017; Yeo et al., 2015; O'Mahoney et al., 2012). For the case of the agriculture sector, Lesschen et al. (2011) found that there are large differences across EU countries in GHG emissions per unit product, which might explain why no strong impact of this sector can be found for Belgium. Similar differences for the contribution of the Residential sector to emissions are found across the European Union, indicating no consistent trend across in sectoral emission contribution of countries. However, I find there is one flaw to a large majority of studies examining the contribution of the Agriculture and Residential sector. It appears to me that a vast majority of decomposition research focusing

[12] In this context it should be noted that, although similar, the definition of the industry sector within the paper of Marrero & Ramos-Real (2013) slightly differs from the one employed within this thesis.

on sectoral emission contribution is only considering CO_2 emissions instead of all air pollutants (see e.g. O'Mahoney et al., 2012; Yeo et al., 2015; Nejat et al., 2015). As mentioned before in the data section, I consider all GHG emissions to achieve the full air emission footprint of the Belgian economy. As an illustrative example, Table 11 showcases the differences between emissions of the Belgian Residential sector when considering either all GHG emissions or only CO_2 emissions.

Table 11: Comparison of Residential Emissions in Belgium

	2015	**2016**	**2017**	**2018**	**2019**
CO_2 emissions	35,326	39,351	70,986	75,928	82,846
GHG emissions	35,545	39,621	71,374	76,314	83,232
Difference (in %)	0.6%	0.7%	0.5%	0.5%	0.5%

Note: emission values are provided in thousand tonnes and have been rounded to three decimal points, *Source*: Eurostat

As can be seen in Table 11, the difference between CO_2 emissions compared to GHG emissions in the Residential sector of Belgium is marginal, with the difference being 0.7 percent at best. This means that for the Residential sector, there is no large difference when examining either CO_2 emissions or GHG emissions in general. Next, the same comparison of emissions is provided for the agriculture sector of the Belgian economy between 2015 and 2019 in Table 12.

Table 12: Comparison of Agriculture Emissions in Belgium

	2015	**2016**	**2017**	**2018**	**2019**
CO_2 emissions	2855,128	3091,194	3157,449	3201,829	3196,563
GHG emissions	12959,483	13068,957	13262,745	13171,256	13163,564
Difference (in %)	354%	323%	320%	311%	312%

Note: emission values are provided in thousand tonnes and have been rounded to three decimal points, *Source*: Eurostat

Comparing Table 12 with Table 11 immediately shows the difference the choice of air emissions has on sectoral emissions. For the agriculture sector in Belgium, the difference between CO_2 emissions and GHG emissions is above 310 percent for all five years shown. This means that if I would have analysed only CO_2 emissions, I would have severely overestimated the role of the Residential sector for emission changes while ignoring a large part of the emission footprint of the agriculture sector. If similar differences for emissions depending on the air pollutant choice exist for countries studied in other decomposition analyses, then it can be expected that on average the effect of the residential sector is overestimated while the effect of the agriculture sector is underestimated. For the case of Belgium, both sectors appear to have little impact on overall emission changes even when considering all GHG emissions. Given the strong potential differences between countries, however, it might be useful to revise some of the decomposition studies considering only CO_2 emissions to see how the obtained results hold when considering all air pollutants. This becomes particularly important when giving advice to policymakers, as an incomplete depiction of the air pollutant situation will inevitably produce skewed results and not allow for a real representation of the emission situation within an economy. After having discussed different aspects of the results, I will now proceed with the policy implications that can be drawn from the analysis conducted within this paper.

5.3 Policy Implications

Based on the results obtained and the discussion highlighting relevant parts of the analysis, important policy implications can be drawn. First, it has been shown that emission reduction efforts in Belgium decreased significantly from the first commitment period of the Kyoto Protocol to the second commitment period. Many of the determinants that fostered a decrease in emissions during the first commitment period are no longer contributing to reducing emissions in the second commitment period (see Figure 5 & 6). The main reason for this development likely lies in the political commitments Belgium agreed upon in the Kyoto Protocol. According to the Burden Sharing Agreement of the Kyoto Protocol, Belgium was required to cut its emissions by 7,5 percent compared to 1990 levels in the first commitment period from 2008-2012 (European Commission, 2019). Belgium exceeded this landmark by far and actually decreased its emissions by almost 14 percent during the first commitment period until 2012 (Belgium, 2021; see Table 7). According to the Doha Amendment, the emission reduction goal for the second commitment period from 2013-2020 was to further cut emissions by 18 percent compared to 1990 levels until 2020 (German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2021). Given the strong progress in reducing GHG emissions during the first period, it is fair to assume that Belgium felt less of a political pressure to maintain the strong negative growth rate of the first commitment period. As a low reduction rate during the second commitment periods sufficed to accomplish the reduction targets established in the Doha amendment, there was no need to increase political efforts to further reduce GHG emissions, at least not from a sheer economic point of view. This lack in political effort to reduce GHG emissions past the agreed amount in the Doha amendment is reflected in the changing contribution of determinants and economic sectors (see Figure 5, 6

& 7). However, it is highly likely that new commitments in form of additional climate protection agreements will follow, and as such Belgium needs to identify which parts of the economy reduce emissions most effectively.

5.3.1 Economic Sectors

Despite not maintaining the strong reduction rate of GHG emissions during the second commitment period, it is still in the interest of the Belgian government to devise policies that reduce emissions in the economically most effective way. As one of the aims of this thesis was to provide an actionable knowledge base for policy implementation, the most effective levers in reducing GHG emissions were identified. In terms of economic sectors, it was observed that the contribution on emissions of most sectors, whether negative or positive, seems to have shrunk over time. The Agriculture sector, the Industry sector, the Energy sector, the Service sector, as well as the Residential sector all decreased in their impact on GHG emissions over time (see Figure 4). The only exception can be found in the contribution of the Transport sector, which appears to remain volatile throughout all time periods, although its effect on emissions was negative for most periods. This volatility makes the Transport sector an interesting point of departure for potential policy implementations, as it appears to be changing dependent on the economic and political circumstances.

The strong CO_2 reduction potential within the Transport sector has already been pointed out by multiple studies. In a study focused on European countries, Andreoni and Galmarini (2012) examined the main drivers of CO_2 emissions in the Belgian sectors of aviation transport and water transport from 2001 to 2008. Interestingly, they find that within the water transport sector the energy intenstiy determinant significantly reduces emissions, whereas the energy intensity effect in the aviation transport sector was among the strongest contributors to emission increases (Andreoni & Galmarini, 2012). On the contrary, they also find that the structural change determinant increases emissions in aviation transport only slightly, whereas it is the single strongest contributor to emission increases in the water transport sector. Andreoni and Galmarini (2012) argue that this development stems from the increasing share of maritime transport activities in the total EU27 GDP. Relating their findings to the results of the present paper indeed suggests a potentially large emission saving potential for the Transport sector, especially given the relative increase of relevance of the Transport sector compared to other sectors. In the case of Belgium, this would mean devising policies that support technological advancements to reduce emission intensity in the transport sector, as well as arranging politicial instruments that can cope with the increasing emissions that might emerge from the rising share of water transport activities within the EU. The strong emission reduction potential of policies addressing the transport sector has also been shown by Gambhir et al. (2015), who find that by spending around $64 billion per year on the transport sector, China’s road transport sector could reduce emissions from a projected 2.08 $GtCO_2$[13] in 2050 to only 1.24 $GtCO_2$ instead. Given that the transport sector in Belgium appears to become one of the most relevant sectors in terms of impact on emissions (see Figure 5), it is considered valuable to perform similar cost-benefit analyses for the Belgian transport sector to evaluate the exact reduction potential of the transport sector. However, the transport sector is not the only part of the economy with great emission reduction potential.

After discussing the results obtained from the decomposition analysis, particular attention should also be paid to the Industry sector. Not only is it the sector that reduced most of its impact on emissions over time (see Figure 5), it is also the sector with the largest impact deviation when comparing the first commitment period to the second commitment period (see Figure 8). While significantly reducing emissions during the first period, the Industry sector is positively contributing to emissions during the second commitment period. It hence seems as if the Industry sector also possesses a great impact potential on GHG emissions, showcased by its strong deviation over time. The underlying driver of this change in the Industry sector is likely to be found in the energy intensity determinant, which changed its contribution to GHG emissions in the same direction as the Industry sector from the first commitment period to the second (see Figure 7). In general, when discussing emission-reducing policies for the industry sector, it is crucial to address the underlying determinant that drove the change in the sector to devise the economically most efficient strategies to reduce emissions. Additionally, addressing the underlying determinants instead of addressing any of the sectors specifically is potentially more effective, as it allows to address the underlying causes that drive GHG emissions in all parts of the economy instead of only focusing on one particular sector. Due to the generally stronger impact of the determinants, I will thus continue with discussing the policy implications of the different determinants and then relate them to the impact of the economic sectors.

5.3.2 Determinants

The analysis conducted within this paper has shown that out of the five determinants under inspection, the effects that have the most emission reduction potential are the energy intensity effect, the emission intensity effect, as well as the structural change effect. The reason those effects have the most reduction potential is due to the fact that they change the most over time (see Figure 4), while other determinants such as the population effect or economic activity

[13] $GtCO_2$ = Gigatonnes of carbon dioxide

effect appear more consistent in their impact on emissions. The energy intensity effect as well as the emission intensity effect are mainly dependent on energy use, with energy intensity indicating the amount of energy consumed to produce one unit of output and emission intensity being an indicator of the embodied emission content of energy sources. The strong emission reduction potential of these two determinants has been widely mentioned in emission literature for a long time (see e.g. Casler & Rose, 1998; Wang et al. 2017), with authors urging politicians to derive supportive strategies fostering the negative contribution of the two determinants on emissions. However, when devising policies supporting improvements in energy intensity or emission intensity, it is important to keep in mind that two different aspects are at the root of the two determinants. While improvements in energy intensity are typically the result of technological progress, improvements in emission intensity are mostly the result of improving emission efficiency by switching to cleaner energy sources (Wang et al., 2017). In the case of Belgium, improved energy intensity during the first commitment period appears to have had a significant impact on reducing emissions (indicated by the energy intensity determinant), whereas in the second period it seems like energy intensity changes actually contributed to emissions (see Figure 5 & 6). This might indicate that Belgium invested a lot into more effective technologies that reduce emissions during the first period, without investing the same amount in the second period. However, investments in sustainable technology are just one policy aspect that might drive down emissions, it could also be that Belgium simply devised stricter regulations for the use of energy. Future studies might look into what led to the strong reduction of energy intensity during the first commitment period and what changed during the second commitment period. As this thesis did only decompose emissions and not energy intensity, it can only presumed what led to the change in energy intensity based on existing literature. Given the large difference between the two time periods, however, it is clear that the energy intensity determinant has a great potential of being influenced by policies, as it can be directly affected through facilitating technological progress focused on emission reduction.

Policy can intervene by subsidizing less energy-intensive technologies or by taxing energy-intensive technologies, respectively, which has been shown to be a major driver of emission reductions (Landis et al., 2019). In their study of 9.734 Swiss households, Landis et al. (2019) find that at the economy-wide level taxing energy is five times as cost-effective as promoting energy savings. Nevertheless, they conclude that there are important trade-offs between efficiency and equity in environmental policy design for Switzerland (Landis et al., 2019). Interestingly, a similar equity-efficiency trade-off has been identified for Belgium by Vandyck and Van Regemorter (2014). Similar to Switzerland, Belgium might substantially decrease emissions by regulating the costs of technologies based on their level of energy intensity. Moreover, financially supporting companies to switch from their outdated production technologies to revised and more emission-friendly technologies bears a huge potential to further dampen GHG emissions. However, the trade-off pointed out in Vandyck and Van Regemorter (2014) also highlights why such environmental policies will hardly be implemented without political pressure coming from commitments such as the Kyoto Protocol, as economic trade-offs pose a substantial obstacle for implementing environmental policies (Landis et al., 2019). Ultimately, future research is required to find ways to minimize this trade-off. Based on the current state of research, it can be assumed that environmental policies tackling energy-related emissions in Belgium are more efficient when energy is taxed instead of promoting energy savings.

Similarly, incentivizing a switch from conventional energy sources to renewable energy sources can greatly improve emission intensity and help building a more sustainable economy. As of now, studies have shown that one of the main obstacle holding companies back from switching to cleaner technologies or energy sources are sunk costs that have been already invested in existing production structures (see e.g. Davidson, 2019). Alleviating this obstacle by financially supporting a switch to cleaner energy sources would lead to a significant decrease in emission intensity, which in turn would drive down GHG emissions by a large margin. As both energy intensity and emission intensity are dependent on the energy use, adressing these determinants is furthermore most effective in those economic sectors which consume a lot of energy. Looking at the energy use of sectors in Appendix D reveals that the Industry sector is the most energy-intensive part of the economy, followed by the Energy sector[14]. Consequently, the biggest potential for policies to reduce GHG emissions in Belgium is by devising policies that foster improvements in energy intensity and emission intensity through subsidizing costs of technological development and from switching to cleaner energy sources. That way, not only would they improve economy-wide emissions from an energy point of view, but also this improvement would be strongest in the sectors that are most dependent on energy and most relevant for changes in emissions.

As mentioned earlier, the structural change effect also has been found to be one of the top three drivers of emission changes, both negative and positive. Altough structural change in general refers to shifting shares of all sectors within the economy, it is mostly connected to the transition away from primary activities towards service activities (see e.g. Duernecker et al., 2017). This switch from energy-intensive industries to service activities is widely thought to substantially reduce emissions. Looking at Figure 4, it appears that especially since 2015 a trend of negative contribution to emissions can be observed for the strucutral change determinant. Additionally, the value added shares of the service sector have been constantly rising since 2015 (see Appendix C), indicating that the transition towards service activities leads to reduced emissions. This result would be in line with the concept of the Environmental Kuznets Curve (EKC) introduced by Panayotou (1993), which is based on Kuznets curve for income and equality relations by Kuznets (1955). This EKC proposes that a transition towards a service economy is one of the main reasons for a reduced environmental impact of economic growth (Panayotou, 1993). However, as Kander (2005) as well as Henriques and Kander (2010) suggest, the real environmental impact of a service transition is limited. Instead of a transition towards service activities, Henriques and Kander (2010) argue that the main reductions in energy intensity come from the manufacturing sector. The point they make is also reflected in my results obtained for Belgium, as the Industry sector that entails all manufacturing activities appears to change the

[14] It should be noted that many studies analyse the energy sector as part of the industry sector.

most in accordance with the energy intensity effect (see Figure 6 & 7). Moreover, even though the structural change determinant appears to reduce emissions in both commitment periods (see Table 7 & 9), its overall impact on emissions throughout time is far more ambiguous than that (see Figure 4). As such, even though it might be possible to affect emissions through policies fostering the restructuring of economic activities, there are other ways to do so more effectively.

Lastly, the economic activity determinant as well as the population determinant have been found to remain fairly consistent in their impact on emissions over time, which is in line with previous findings of many other scholars (e.g. Albrecht et al., 2002; Fernández González et al., 2014; Moutinho et al., 2015; Liu et al., 2007). Although this development is not necessarily indicating a general inability of environmental policies to address these determinants, it does suggest that the impact of these determinants is somewhat constant and seems to be dependent on variables that are hardly to be addressed from a policy point of view (such as for example the number of residents in a country or the overall GVA per capita of residents). Consequently, devising policies that address those determinants will be less successful than policies that address determinants that appear to be more sensitive to policy changes. Overall, the results obtained imply that emission-related policies in Belgium are most effective when addressing energy intensity and emission intensity as well as regulations of the industry sector. There exist other potential parts of the economy that policies might tackle successfully, but further research is required to ensure their viability. The next chapter will conclude the paper and summarize the findings and results that the decomposition analysis produced. Additionally, the results will be put into context of my research aims and objectives and a short outlook on potential future research will be given.

6 Conclusion

Within this paper, the development of greenhouse gas emissions in Belgium was analysed and changes to emissions were decomposed into the contribution of the underlying determinants and economic sectors. Moreover, the time series results obtained for Belgium in the years from 2008 to 2018 were aggregated into two commitment periods relating to the ones established in the Kyoto Protocol. As such, this thesis provided the first two-step application of the LMDI I model to decompose GHG emission changes of Belgium in the context of the two commitment periods of the Kyoto Protocol. Amongst other aspects, it was found that Belgium decreased its emission reduction efforts significantly from the first commitment period to the second commitment period. In this context, the results suggested that energy intensity, emission intensity, as well as structural change had the largest effect on emission changes between the two periods. Additionally, the industry sector was found to play a pivotal role in explaining the emission changes observed in the two periods. However, not only the two commitment periods were observed, but they were also put into context of time series results to examine yearly changes in more detail. The time series decomposition revealed that out of the five determinants, the energy intensity effect, the emission intensity effect, and the structural change effect were most volatile over time. The population determinant and the economic activity determinant on the other hand remained rather constant in their positive contribution to emissions. Additionally, it was found that the impact of the different economic sectors on emissions appears to have decreased substantially over time. This indicates that the relative importance of sectoral contributions to emission changes has sunk. Comparing the time series results with the results obtained for the aggregated time periods furthermore emphasized the need to not discard the in-between years when analysing longer time periods. It was shown that significant differences in the impact of emission contributions exist between aggregated and time series results, which might lead to wrongful conclusions if only one of the two approaches is considered. Lastly, the need for analysing the full air emission footprint was reinforced and it was shown that only considering specific air pollutants results in a skewed picture of reality that over- or underestimates parts of the economy depending on the air pollutant used.

6.1 Research Aims & Objectives

One of the most important aspects when evaluating the quality of my analsis is its success in working towards the research aims and objectives. As such, it is now time to evaluate how successful the chosen research design was in achieveing the desired aims and objectives. As a quick reminder, the two research questions mentioned in the thesis outline are stated again below.

1. *How do the determinants and economic sectors affect greenhouse gas emissions in Belgium between 2008 and 2018?*

2. *What are the driving forces of greenhouse gas emission changes within and across the two commitment periods of the Kyoto Protocol in Belgium?*

In alignment with the two research questions, the present paper had the aim to produce holistic results that showcase not only the general development of emission determinants and sectors in Belgium throughout time, but also to put them into the context of the first legally binding climate protection agreement. Moreover, the results are supposed to serve as an actionable knowledge base when trying to affect emission changes from a policy point of view, as policies will be most effective when the main reason for the emission change is addressed. As such, the objective for my decomposition analysis was to analyse the underlying forces of reductions or increases of GHG emissions in Belgium from 2008 to 2018 and to relate these results to the context of the two commitment periods of the Kyoto Protocol. The obtained results indicate that most determinants (aside from the economic activity effect and the population effect) are ambiguous in their impact on emissions over time, whereas the impact of the economic sectors appears to shrink over time. It was shown that population and economic activity increase emissions quite steadily over time, whereas the remaining three determinants strongly fluctuate between increasing and decreasing emissions. After aggregating the time series results to the two commitment periods, it was shown that during the first commitment period Belgium strongly reduced emissions, which was driven mainly by the energy intensity determinant and the industry sector. During the second commitment period, Belgium did not decrease emissions at the same rate, and energy intensity changes actually contributed to an increase in emissions. However, their positive contribution was offset by the strong negative effect of structural change and emission intensity. Putting these results into context with the results obtained from the time series decomposition clearly showed the differences between the two approaches and helped in preventing wrongful conclusions by identifying the underlying yearly contributions within the commitment periods. As such, the conducted analysis was successful in isolating the driving forces of emissions both on a time series basis as well as on an aggregated basis, allowing policymakers to comprehend the impact of the driving forces on multiple scales. Consequently, the development of emissions can be understood from on a yearly basis from one year to the other as well as in light of the first internationally binding agreement on climate protection. Additionally, the magnitude of factors contributing to emission changes was clearly presented, allowing policymakers to draw from the results and devise policies considering the relative impact of each factor. Moreover, it was shown that the chosen research design also helped in preventing wrongful conclusions due to a limited choice of air pollutants. Choosing GHG emissions as the emission variable under observation allowed to produce holistic results that really showcase the full air emission footprint of Belgium and how this footprint behaves between 2008 and 2018. Overall, it was clearly shown how determinants and sectors develop between 2008 and 2018 and what forces drove emission changes within and across the two commitment periods of the Kyoto Protocol. As such, the chosen methodology and research design was successful in achieving the overall aims and objectives of the thesis and generated valuable insights for future research and policy proposals.

6.2 Practical Implications

After having discussed and interpreted the decomposition results, important conclusions have been drawn in terms of practical implications for policy. First, it was clearly shown that the sectoral contribution to emissions has decreased over time. This implies that devising policies that address only specific sectors become relatively less efficient, as the impact of sectors in general has declined. Consequently, policies have a greater impact potential when addressing the underyling determinants of emission changes, which has been shown to most effectively be the energy intensity determinant and the emission intensity determinant. Addressing these determinants furthermore has the advantage of creating a positive impact in all parts of the economy, as energy-related policies are not confined to a single sector. In terms of energy-related policies, the exisiting research suggests that taxing energy might be more cost-effective than promoting energy savings (Landis et al., 2019). Nevertheless, it seems as if environmental and energy policies in Belgium face an equity-efficiency trade-off, which often hinders policies from being implemented when there is no political pressure. This behaviour was also reflected in the differences from the first commitment period to the second commitment period. Such an economic trade-off is also the reason why many industries do not switch to cleaner energy sources. Here, the Belgian government could intervene by subsidizing a switch to cleaner energy sources and production technologies, which would significantly reduce the abovementioned trade-off from a company point of view. By doing so, Belgium would actively facilitate improvements in energy intensity and emission intensity and thus further drive down emissions. Given the obtained results, it can be expected that the effect of such policies would be most significant in the industry and energy sector, as those are the most energy-intensive parts of the economy (see Appendix D). In terms of research design, it was shown that it is imperative for decomposition analyses to not discard the in-between years of time periods, as this might lead to wrongful conclusions with regards to the driving forces of emissions. More specifically, when decomposing sectoral emission changes, it is also of great importance to consider all air pollutants being emitted to ensure an accurate representation of the air emission footprint of the economy. Focusing on only a particular air pollutant has been shown to lead to substantial differences in the sectoral contribution to emissions and thus lead to a wrongful representation of the actual emission situation within an economy.

6.3 Future Research

Aside from providing new insights into the emission dynamics of Belgium between 2008 and 2018, the analysis conducted within this paper has also highlighted the shortcomings of existing research. First, it would be extremely beneficial to have a larger body of literature decomposing emission changes during the two commitment periods for multiple countries. As mentioned before, to the best of my knowledge is this the first application of a decomposition model analysing emissions for the two commitment periods of the Kyoto Protocol specifically. Having a decomposition of emission changes during the Kyoto Protocol commitment periods for all European countries, for instance, would allow for a comparison between successful and less successful countries in reducing emissions and provide an evaluation of what drove their success or failure. This would clearly show what parts of the economy are the most relevant ones for reducing emissions in Europe and would theoretically enable policymakers to devise European-wide policies that facilitate a reduction of emissions. In terms of research concerning Belgium, an interesting aspect for future research would be to decompose emission changes in more detail by differentiating between more sectors of the economy. That way, policymakers could address emission drivers on a more sophisticated level and tailor policies to the respective parts of the economy. In this context it should also be noted that based on the results of this study the transport sector in Belgium appears to be growing in its relative importance for mitigating GHG emissions. Providing a cost-benefit analysis for emission-reducing investments in the transport sector, such as Gambhir et al. (2015) have done for the Chinese transport sector, might produce clear scenarios and objectives policymakers can work towards.

Given the discrepancy between sectoral emission contributions based on the chosen air pollutant, future research is also advised to revise some of the existing decomposition literature that limited its sectoral decomposition to only include particular air pollutants. By doing so, a more complete picure of the emission footprint can be achieved and previous findings and implications for policy can be confirmed or updated depending on new results. Lastly, it would be worth studying energy intensity and emission intensity of Belgium in more detail. As was shown in this paper, these two determinants are important contributors to changes in GHG emissions and appear to be effective levers for policy to reduce emissions in Belgium. It would hence be of great value to decompose energy intensity and emission intensity for the two commitment periods to examine what exactly drove the changes in those two determinants and how policy can further regulate their development.

6.4 Chapter Summary

Within this thesis, the first chapter provided an introduction to the topic at hand as well as an outline of the overall thesis scope and purpose. Afterwards, a comprehensive review of previous research and relevant literature was pursued and presented in the second chapter. The third chapter then discussed the quality and reliability of the data sources used, whereas the fourth chapter explained the LMDI methodology and its components in detail. The fifth chapter then presented the obtained results and interpreted them based on a sophisticated discussion which was followed by mentioning the implications of the results for policy proposals. Lastly, this chapter has concluded and summarized the most important aspects and findings of my analysis and has provided an outlook of what future research might want to look into.

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Appendix A

A.1. A*10 to A*64 hierarchy of economic activities

	Description	A*64	A*38	A*21	A*10
1	Crop and animal production, hunting and related service activities	01	A	A	A
2	Forestry and logging	02			
3	Fishing and aquaculture	03			
4	Mining and quarrying	05-09	B	B	B-E
5	Manufacture of food products, beverages and tobacco	10-12	CA	C	
6	Manufacture of textiles, wearing apparel, leather and related products	13-15	CB		
7	Manufacture of wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	16	CC		
8	Manufacture of paper and paper products	17			
9	Printing and reproduction of recorded media	18			
10	Manufacture of coke and refined petroleum products	19	CD		
11	Manufacture of chemicals and chemical products	20	CE		
12	Manufacture of basic pharmaceutical products and pharmaceutical preparations	21	CF		
13	Manufacture of rubber and plastics products	22	CG		

14	Manufacture of other non-metallic mineral products	23			
15	Manufacture of basic metals	24	CH		
16	Manufacture of fabricated metal products, except machinery and equipment	25			
17	Manufacture of computer, electronic and optical products	26	CI		
18	Manufacture of electrical equipment	27	CJ		
19	Manufacture of machinery and equipment n.e.c.	28	CK		
20	Manufacture of motor vehicles, trailers and semi-trailers	29	CL		
21	Manufacture of other transport equipment	30			
22	Manufacture of furniture, other manufacturing	31-32	CM		
23	Repair and installation of machinery and equipment	33			
24	Electricity, gas, steam and air conditioning supply	35	D	D	
25	Water collection, treatment and supply	36	E	E	
26	Sewerage, waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	37-39			
27	Construction	41-43	F	F	F
28	Wholesale and retail trade and repair of motor vehicles and motorcycles	45	G	G	G-I
29	Wholesale trade, except of motor vehicles and motorcycles	46			
30	Retail trade, except of motor vehicles and motorcycles	47			

31	Land transport and transport via pipelines	49	H	H	
32	Water transport	50			
33	Air transport	51			
34	Warehousing and support activities for transportation	52			
35	Postal and courier activities	53			
36	Accommodation and food service activities	55-56	I	I	
37	Publishing activities	58	JA	J	J
38	Audiovisual and broadcasting activities	59-60			
39	Telecommunications	61	JB		
40	IT and other information services	62-63	JC		
41	Financial service activities, except insurance and pension funding	64	K	K	K
42	Insurance, reinsurance and pension funding, except compulsory social security	65			
43	Activities auxiliary to financial service and insurance activities	66			
44	Real estate activities	68	L	L	L
45	Legal and accounting activities; activities of head offices; management consultancy activities	69-70	MA	M	M-N
46	Architectural and engineering activities; technical testing and analysis	71			
47	Scientific research and development	72	MB		
48	Advertising and market research	73	MC		
49	Other professional, scientific and technical activities; veterinary activities	74-75			

50	Rental and leasing activities	77	N	N	
51	Employment activities	78			
52	Travel agency, tour operator, reservation service and related activities	79			
53	Security and investigation activities; services to buildings and landscape activities; office administrative, office support and other business support activities	80-82			
54	Public administration and defence; compulsory social security	84	O	O	O-Q
55	Education	85	P	P	
56	Human health activities	86	QA	Q	
57	Residential care and social work activities	87-88	QB		
58	Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities	90-92	R	R	R-U
59	Sports activities and amusement and recreation activities	93			
60	Activities of membership organizations	94	S	S	
61	Repair of computers and personal and household goods	95			
62	Other personal service activities	96			
63	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	97-98	T	T	
64	Activities of extraterritorial organizations and bodies	99	U	U	

Appendix B

B.1. Gross Value Added for Belgium (2008-2018)

Gross Value Added

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
INDUSTRY SECTOR (chain linked volumes 2015, million euro)											
Belgium	67623,60	63431,60	65661,90	66686,70	65616,90	65613,80	67627,10	68601,20	68219,50	69483,20	70666,70
TRANSPORT SECTOR (chain linked volumes 2015, million euro)											
Belgium	8422,70	8094,30	8775,10	8642,00	8610,60	8362,70	8788,10	8988,90	8776,50	8813,50	9474,80
ENERGY SECTOR (chain linked volumes 2015, million euro)											
Belgium	7201,20	6341,30	7191,90	7001,50	6477,60	6354,80	6795,10	8111,80	7756,70	7118,00	6077,60
SERVICE SECTOR (chain linked volumes 2015, million euro)											
Belgium	260787,40	258706,10	264070,90	269897,70	274486,40	276563,80	279261,20	284314,90	288957,00	294144,90	300896,60
AGRICULTURE SECTOR (chain linked volumes 2015, million euro)											
Belgium	2633,50	2471,00	2737,00	2792,80	2797,60	2400,90	2406,70	2860,30	2656,80	2772,30	2351,70
RESIDENTIAL SECTOR (chain linked volumes 2015, million euro)											
Belgium	637,20	596,80	525,20	506,20	531,10	446,00	431,20	424,50	451,10	462,90	470,00
TOTAL GROSS VALUE ADDED											
Belgium	347305,6	339641,1	348962	355526,9	358520,2	359742	365309,4	373301,6	376817,6	382794,8	389937,4

B.2. Greenhouse Gas Emissions for Belgium (2008-2018)

Greenhouse Gas Emissions

	INDUSTRY SECTOR (GHG, in thousand tonnes)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	44223,09836	32839,275	37833,463	36901,800	34339,557	34530,648	33895,893	33706,707	34117,213	34393,173	34632,670
	TRANSPORT SECTOR (GHG, in thousand tonnes)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	13661,94332	12593,1644	11996,4569	11198,1056	10479,8860	9122,9825	9994,3406	11825,2067	11652,1044	10571,3271	10002,7469
	ENERGY SECTOR (GHG, in thousand tonnes)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	27106,83003	27673,5151	28509,3706	24971,0133	24697,9140	23367,8393	22595,4261	23353,0520	22339,9848	22235,5389	22493,0787
	SERVICE SECTOR (GHG, in thousand tonnes)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	15311,13609	15982,0056	16881,3592	15391,9019	15556,8923	15434,3193	13766,4722	14769,8894	14624,9835	14862,5863	14768,7551
	AGRICULTURE SECTOR (GHG, in thousand tonnes)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	12258,22766	12400,6603	12499,8182	12090,0642	11946,0468	12035,7078	12381,8233	12959,4828	13068,9577	13262,7453	13171,2562
	RESIDENTIAL SECTOR (GHG, in thousand tonnes)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	33,93488	36,3045	38,2782	32,6590	35,6276	34,1807	31,1935	35,5447	39,6216	71,3742	76,3146
	TOTAL GREENHOUSE GAS EMISSIONS										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	112595,170	101524,925	107758,746	100585,544	97055,924	94525,678	92665,148	96649,883	95842,865	95396,745	95144,822

B.3. Energy Use for Belgium (2008-2018)

Energy Use

	INDUSTRY SECTOR (in TJ)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	504136,70	389313,30	464428,10	473793,50	442602,40	454352,00	447676,50	466828,60	471467,00	467226,70	491430,70
	TRANSPORT SECTOR (in TJ)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	178410,30	165916,10	158993,60	147409,80	137606,70	120318,40	132310,60	156165,10	154384,60	140401,90	133226,70
	ENERGY SECTOR (in TJ)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	367040,30	385119,30	393411,20	335228,20	324015,50	284872,10	254004,20	269545,20	258174,10	263402,10	266430,00
	SERVICE SECTOR (in TJ)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	189798,60	202629,20	222020,80	194478,40	201186,30	203120,00	181412,50	194897,00	197439,30	198906,60	199522,70
	AGRICULTURE SECTOR (in TJ)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	29185,00	31571,50	35105,70	30224,90	31741,80	33643,70	35418,10	43236,30	46898,30	47833,70	48762,10
	RESIDENTIAL SECTOR (in TJ)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	610,10	683,30	700,80	583,60	653,40	588,40	532,10	604,80	675,90	1189,30	1257,30
	TOTAL ENERGY USE										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	1269181,00	1175232,70	1274660,20	1181718,40	1137806,10	1096894,60	1051354,00	1131277,00	1129039,20	1118960,30	1140629,50

B.4. Population for Belgium (2008-2018)

	POPULATION										
	TOTAL POPULATION (in number of people)										
	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Belgium	10666866	10753080	10839905	11000638	11075889	11137974	11180840	11237274	11311117	11351727	11398589

Appendix C

C.1. Intermediary Inputs for Period 2008-2009

		Population			GVA per capita
P, 0	**2008**	10666866	*U, T*	**2008**	0,032559292
P, T	**2009**	10753080	*U, 0*	**2009**	0,031585471

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, 0	**2008**	0,007582659	0,194709213	0,020734477	0,750887403	0,024251553	0,001834695	
S_i, T	**2009**	0,007275327	0,186760672	0,018670591	0,76170434	0,023831921	0,001757149	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, 0	**2008**	11,08220999	7,455040844	50,96932456	0,72779053	21,18207938	0,957470182	92,3739155
I_i, T	**2009**	12,77681101	6,137529244	60,73191617	0,783240905	20,49789358	1,144939678	102,072331

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, 0	**2008**	0,42001808	0,08772045	0,073852463	0,080670437	0,076575979	0,055621832	
K_i, T	**2009**	0,392780208	0,084351793	0,071856994	0,078873161	0,075900798	0,053131187	

C.2. Intermediary Inputs for Period 2009-2010

		Population			GVA per capita
P, 0	**2009**	10753080	*U, T*	**2009**	0,031585471
P, T	**2010**	10839905	*U, 0*	**2010**	0,032192349

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, 0	**2009**	0,007275327	0,186760672	0,018670591	0,76170434	0,023831921	0,001757149	
S_i, T	**2010**	0,007843261	0,188163468	0,020609407	0,756732538	0,025146291	0,001505035	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, 0	**2009**	12,77681101	6,137529244	60,73191617	0,783240905	20,49789358	1,144939678	102,072331
I_i, T	**2010**	12,82634271	7,07302256	54,70198418	0,840762083	18,11872229	1,334348819	94,8951826

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, 0	**2009**	0,392780208	0,084351793	0,071856994	0,078873161	0,075900798	0,053131187	
K_i, T	**2010**	0,356062355	0,081462476	0,072467105	0,076035034	0,075452452	0,054620691	

C.3. Intermediary Inputs for Period 2010-2011

		Population			GVA per capita
P, 0	**2010**	10839905	*U, T*	**2010**	0,032192349
P, T	**2011**	11000638	*U, 0*	**2011**	0,032318753

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, *0*	**2010**	0,007843261	0,188163468	0,020609407	0,756732538	0,025146291	0,001505035	
S_i, *T*	**2011**	0,007855383	0,187571461	0,019693306	0,759148464	0,024307584	0,001423802	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, *0*	**2010**	12,82634271	7,07302256	54,70198418	0,840762083	18,11872229	1,334348819	94,8951826
I_i, *T*	**2011**	10,82243626	7,104767517	47,87948297	0,720563384	17,05737098	1,152903991	84,7375251

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, *0*	**2010**	0,356062355	0,081462476	0,072467105	0,076035034	0,075452452	0,054620691	
K_i, *T*	**2011**	0,400003447	0,07788583	0,074489596	0,079144531	0,075965815	0,055961326	

C.4. Intermediary Inputs for Period 2011-2012

		Population			GVA per capita
P, 0	**2011**	11000638	*U, T*	**2011**	0,032318753
P, T	**2012**	11075889	*U, 0*	**2012**	0,032369429

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, *0*	**2011**	0,007855383	0,187571461	0,019693306	0,759148464	0,024307584	0,001423802	
S_i, *T*	**2012**	0,007803187	0,183021487	0,018067601	0,765609302	0,024017057	0,001481367	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, *0*	**2011**	10,82243626	7,104767517	47,87948297	0,720563384	17,05737098	1,152903991	84,7375251
I_i, *T*	**2012**	11,34608236	6,74525008	50,02091824	0,73295544	15,98108146	1,230276784	86,0565644

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, *0*	**2011**	0,400003447	0,07788583	0,074489596	0,079144531	0,075965815	0,055961326	
K_i, *T*	**2012**	0,37635064	0,077585565	0,076224483	0,077325803	0,076158254	0,0545264	

C.5. Intermediary Inputs for Period 2012-2013

		Population			GVA per capita
P, 0	**2012**	11075889	*U, T*	**2012**	0,032369429
P, T	**2013**	11137974	*U, 0*	**2013**	0,032298693

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, 0	**2012**	0,007803187	0,183021487	0,018067601	0,765609302	0,024017057	0,001481367	
S_i, T	**2013**	0,00667395	0,182391269	0,017664882	0,768783739	0,023246382	0,001239777	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, 0	**2012**	11,34608236	6,74525008	50,02091824	0,73295544	15,98108146	1,230276784	86,0565644
I_i, T	**2013**	14,01295348	6,924640853	44,8278624	0,734441745	14,38750643	1,319282511	82,2066874

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, 0	**2012**	0,37635064	0,077585565	0,076224483	0,077325803	0,076158254	0,0545264	
K_i, T	**2013**	0,357740314	0,075999772	0,082029231	0,075986211	0,075823668	0,058090857	

C.6. Intermediary Inputs for Period 2013-2014

		Population			GVA per capita
P, 0	**2013**	11137974	*U, T*	**2013**	0,032298693
P, T	**2014**	11180840	*U, 0*	**2014**	0,032672805

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, 0	**2013**	0,00667395	0,182391269	0,017664882	0,768783739	0,023246382	0,001239777	
S_i, T	**2014**	0,006588114	0,185122803	0,018600945	0,764451175	0,024056594	0,001180369	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, 0	**2013**	14,01295348	6,924640853	44,8278624	0,734441745	14,38750643	1,319282511	82,2066874
I_i, T	**2014**	14,71645822	6,619779645	37,38049477	0,649615844	15,05565481	1,233998145	75,6560014

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, 0	**2013**	0,357740314	0,075999772	0,082029231	0,075986211	0,075823668	0,058090857	
K_i, T	**2014**	0,349590275	0,075715148	0,0889569	0,075884915	0,075536961	0,058623379	

C.7. Intermediary Inputs for Period 2014-2015

		Population			GVA per capita
P, 0	**2014**	11180840	*U, T*	**2014**	0,032672805
P, T	**2015**	11237274	*U, 0*	**2015**	0,033219943

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, *0*	**2014**	0,006588114	0,185122803	0,018600945	0,764451175	0,024056594	0,001180369	
S_i, *T*	**2015**	0,007662169	0,183768835	0,021729883	0,761622506	0,024079457	0,00113715	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, *0*	**2014**	14,71645822	6,619779645	37,38049477	0,649615844	15,05565481	1,233998145	75,6560014
I_i, *T*	**2015**	15,11600182	6,804962595	33,22877783	0,685496961	17,37310461	1,424734982	74,6330788

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, *0*	**2014**	0,349590275	0,075715148	0,0889569	0,075884915	0,075536961	0,058623379	
K_i, *T*	**2015**	0,299736165	0,072203604	0,086638723	0,075783051	0,075722467	0,058771065	

C.8. Intermediary Inputs for Period 2015-2016

		Population			GVA per capita
P, 0	**2015**	11237274	*U, T*	**2015**	0,033219943
P, T	**2016**	11311117	*U, 0*	**2016**	0,033313916

		Value Added Shares (S_i=Q_i/Q)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, *0*	**2015**	0,007662169	0,183768835	0,021729883	0,761622506	0,024079457	0,00113715	
S_i, *T*	**2016**	0,007050626	0,181041172	0,02058476	0,766835201	0,02329111	0,001197131	

		Energy Intensity (I_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, *0*	**2015**	15,11600182	6,804962595	33,22877783	0,685496961	17,37310461	1,424734982	74,6330788
I_i, *T*	**2016**	17,65217555	6,911029838	33,28401253	0,683282634	17,59067966	1,498337397	77,6195176

		Emission Intensity (K_i=E_i/Q_i)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, *0*	**2015**	0,299736165	0,072203604	0,086638723	0,075783051	0,075722467	0,058771065	
K_i, *T*	**2016**	0,278665915	0,072363947	0,086530697	0,074073315	0,075474526	0,058620432	

C.9. Intermediary Inputs for Period 2016-2017

		Population			GVA per capita
P, 0	**2016**	11311117	*U, T*	**2016**	0,033313916
P, T	**2017**	11351727	*U, 0*	**2017**	0,033721283

		Value Added Shares ($S_i=Q_i/Q$)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, *0*	**2016**	0,007050626	0,181041172	0,02058476	0,766835201	0,02329111	0,001197131	
S_i, *T*	**2017**	0,007242261	0,181515527	0,018594819	0,768414043	0,023024085	0,001209264	

		Energy Intensity ($I_i=E_i/Q_i$)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, *0*	**2016**	17,65217555	6,911029838	33,28401253	0,683282634	17,59067966	1,498337397	77,6195176
I_i, *T*	**2017**	17,2541572	6,724311776	37,00507165	0,676219781	15,9303228	2,569237416	80,1593206

		Emission Intensity ($K_i=E_i/Q_i$)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, *0*	**2016**	0,278665915	0,072363947	0,086530697	0,074073315	0,075474526	0,058620432	
K_i, *T*	**2017**	0,27726781	0,073611318	0,084416711	0,074721434	0,075293334	0,060013605	

C.10. Intermediary Inputs for Period 2017-2018

		Population			GVA per capita
P, 0	**2017**	11351727	*U, T*	**2017**	0,033721283
P, T	**2018**	11398589	*U, 0*	**2018**	0,034209269

		Value Added Shares ($S_i=Q_i/Q$)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
S_i, *0*	**2017**	0,007242261	0,181515527	0,018594819	0,768414043	0,023024085	0,001209264	
S_i, *T*	**2018**	0,006030968	0,181225756	0,015586092	0,771653604	0,024298259	0,001205322	

		Energy Intensity ($I_i=E_i/Q_i$)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
I_i, *0*	**2017**	17,2541572	6,724311776	37,00507165	0,676219781	15,9303228	2,569237416	80,1593206
I_i, *T*	**2018**	20,73483012	6,954204739	43,83802817	0,6630939	14,06116224	2,675106383	88,9264256

		Emission Intensity ($K_i=E_i/Q_i$)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
K_i, *0*	**2017**	0,27726781	0,073611318	0,084416711	0,074721434	0,075293334	0,060013605	
K_i, *T*	**2018**	0,270112572	0,070473152	0,084423971	0,074020425	0,075080647	0,060697192	

Appendix D

D.1. Decomposition Results for Period 2008-2009

		LMDI Decomposition Result (2008-2009)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
D_{act}		0,996506025	0,989200385	0,992254795	0,995568717	0,996282285	0,999990034	0,97014519
D_{str}		0,995242226	0,985206507	0,97350989	1,002094049	0,997861291	0,999985826	0,95448463
D_{int}		1,016536428	0,932823285	1,045895103	1,01079699	0,995980749	1,000058689	0,99850634
D_{pop}		1,000928308	1,002882704	1,002063377	1,00117804	1,000987893	1,000002642	1,00806745
D_{eint}		0,992301527	0,986094795	0,993010735	0,996710113	0,998914282	0,999984964	0,96740166
D_{tot}	**TOTAL**	1,001332474	0,899041491	1,005311934	1,006291593	0,990057858	1,000022154	

D.2. Decomposition Results for Period 2009-2010

		LMDI Decomposition Result (2009-2010)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
D_{act}		1,002267591	1,006438567	1,005123297	1,002993092	1,002238823	1,000006783	1,01920702
D_{str}		1,008985943	1,002526689	1,026883561	0,998972168	1,006328184	0,999944805	1,04417024
D_{int}		1,000460595	1,04900357	0,972312303	1,011190982	0,985607132	1,000054562	1,0170527
D_{pop}		1,000957571	1,002715652	1,002161716	1,001263675	1,00094543	1,000002866	1,00807159
D_{eint}		0,988387392	0,988315283	1,002272798	0,994261694	0,999304076	1,000009854	0,97277253
D_{tot}	**TOTAL**	1,000948323	1,048898551	1,008022146	1,008634194	0,99431217	1,000018867	

D.3. Decomposition Results for Period 2010-2011

		LMDI Decomposition Result (2010-2011)						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
D_{act}		1,000462769	1,001407201	1,001005369	1,000607035	1,000436372	1,000001332	1,00392589
D_{str}		1,000182346	0,998869884	0,988408637	1,00049372	0,99623065	0,999981141	0,98421666
D_{int}		0,980143629	1,001608196	0,966418528	0,976392856	0,993302393	0,999950321	0,92010489
D_{pop}		1,001739255	1,005295659	1,003781368	1,002281912	1,001639986	1,000005003	1,01482545
D_{eint}		1,013833242	0,984018013	1,00708334	1,006226107	1,000755174	1,000008242	1,01172386
D_{tot}	**TOTAL**	0,996072745	0,991092877	0,966590958	0,98579812	0,992362516	0,999946039	

D.4. Decomposition Results for Period 2011-2012

		LMDI Decomposition Result (2011-2012)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
D_{act}		1,000190579	1,000564733	1,000393859	1,000245396	1,00017182	1,000000541	1,00156786
D_{str}		0,999189464	0,991190394	0,978578367	1,001328056	0,998682364	1,000013687	0,96919296
D_{int}		1,005763518	0,981462409	1,011057537	1,002673936	0,99287852	1,000022431	0,99359867
D_{pop}		1,000829508	1,002459573	1,00171488	1,001068201	1,000747831	1,000002354	1,00683995
D_{eint}		0,992614063	0,998609103	1,005803261	0,996365851	1,000277468	0,99999103	0,99362934
D_{tot}	TOTAL	0,998543546	0,974402374	0,997239939	1,001671165	0,992757676	1,000030043	

D.5. Decomposition Results for Period 2012-2013

		LMDI Decomposition Result (2012-2013)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
D_{act}		0,999726176	0,999213839	0,999451398	0,999646156	0,999776525	0,999999203	0,9978151
D_{str}		0,980621351	0,99876072	0,994361591	1,000669598	0,996673505	0,999935136	0,97123111
D_{int}		1,02677995	1,009480742	0,972879649	1,00032777	0,989325569	1,00002545	0,9979922
D_{pop}		1,000699997	1,002011555	1,001403119	1,000904686	1,000571234	1,000002037	1,00560445
D_{eint}		0,993671516	0,992603387	1,018580373	0,997176867	0,999550278	1,000023072	1,00138425
D_{tot}	TOTAL	1,000936502	1,001996985	0,986209955	0,998721154	0,985933763	0,999984895	

D.6. Decomposition Results for Period 2013-2014

		LMDI Decomposition Result (2013-2014)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
D_{act}		1,001503287	1,004218613	1,002831569	1,001796199	1,001176046	1,000004019	1,01157996
D_{str}		0,998312949	1,0054487	1,012758199	0,999119706	1,00350266	0,999982862	1,01920372
D_{int}		1,006409848	0,983676324	0,95637269	0,981056767	1,004643605	0,999976677	0,93314749
D_{pop}		1,000501168	1,001405139	1,000943576	1,000598761	1,000392115	1,000001341	1,00384767
D_{eint}		0,996998514	0,99862938	1,020105902	0,999792148	0,999613429	1,000003185	1,01504968
D_{tot}	TOTAL	1,003704965	0,993240813	0,991781009	0,982337504	1,009353619	0,999968084	

D.7. Decomposition Results for Period 2014-2015

		LMDI Decomposition Result (2014-2015)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
D_{act}		1,002225436	1,0059488	1,004039112	1,002505772	1,001911686	1,000005847	1,01674207
D_{str}		1,020421491	0,997381734	1,038458702	0,999441511	1,000109251	0,999986867	1,05640236
D_{int}		1,003592053	1,009902283	0,971828009	1,008134702	1,016600972	1,000050604	1,00952491
D_{pop}		1,000674143	1,001799718	1,001222782	1,00075899	1,000579163	1,000001773	1,00504621
D_{eint}		0,979615887	0,983182936	0,993611368	0,9997976	1,000282118	1,000000886	0,95706555
D_{tot}	TOTAL	1,006122192	0,998003074	1,008037172	1,010658469	1,019533186	1,000045976	

D.8. Decomposition Results for Period 2015-2016

		LMDI Decomposition Result (2015-2016)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
***D** act*		1,000382039	1,000995801	1,000670661	1,00043146	1,000344583	1,000001102	1,00282869
***D** str*		0,988815775	0,994744862	0,987233343	1,001042133	0,995948398	1,000020053	0,96815481
***D** int*		1,021194448	1,005464398	1,000394266	0,999506045	1,001519094	1,00001965	1,02825192
***D** pop*		1,000886036	1,002310427	1,001555715	1,001000688	1,000799148	1,000002555	1,00657098
***D** eint*		0,990192521	1,000781886	0,999703932	0,996521416	0,999600075	0,999998999	0,9868314
***D** tot*	TOTAL	1,001138098	1,004274286	0,989529371	0,998495552	0,998203073	1,000042359	

D.9. Decomposition Results for Period 2016-2017

		LMDI Decomposition Result (2016-2017)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
***D** act*		1,00167485	1,004363564	1,002836955	1,001875763	1,001412266	1,000006857	1,01222674
***D** str*		1,003699199	1,000937861	0,976581057	1,000317184	0,998661978	1,00000569	0,98011651
***D** int*		0,996864838	0,99023605	1,025009702	0,998399194	0,988553734	1,000304297	0,99894051
***D** pop*		1,000493572	1,001284709	1,000835697	1,000552741	1,000416227	1,000002022	1,00358986
***D** eint*		0,999307705	1,006141355	0,99425144	1,001344137	0,999720945	1,000013252	1,00074256
***D** tot*	TOTAL	1,002028706	1,00289019	0,99890829	1,002487964	0,988760757	1,000332127	

D.10. Decomposition Results for Period 2017-2018

		LMDI Decomposition Result (2017-2018)						
		Agriculture	Industry	Energy	Services	Transport	Residential	TOTAL
***D** act*		1,001995191	1,005218323	1,003378342	1,002236791	1,001552161	1,000011132	1,01447069
***D** str*		0,974928378	0,999421393	0,959413662	1,000654454	1,005831509	0,99999747	0,94088278
***D** int*		1,025821085	1,012252513	1,040577961	0,996956392	0,986617422	1,000031287	1,06285407
***D** pop*		1,000571689	1,001493512	1,000967532	1,00064086	1,000444816	1,000003192	1,00412805
***D** eint*		0,996379455	0,984341314	1,000020189	0,998535244	0,999694683	1,000008776	0,97907021
***D** tot*	TOTAL	0,999040155	1,002517021	1,002706899	0,999015594	0,994049726	1,000051858	

Appendix E

E.1. Weight Coefficient for each Economic Sector

		$w_i = ((C^T{}_i-C^0{}_i)/(\ln(C^T{}_i)-\ln(C^0{}_i)))/(C^T-C^0)/(\ln(C^T)-\ln(C^0))$						
		Agriculture	**Industry**	**Energy**	**Services**	**Transport**	**Residential**	**TOTAL**
Numerator w	/	13216,94798	34512,78326	22364,06161	14815,62115	10284,4176	73,81682787	
Denominator w	/	95270,7278	95270,7278	95270,7278	95270,7278	95270,7278	95270,7278	
w_i		0,138730419	0,362260099	0,234742214	0,155510738	0,107949397	0,000774811	

Appendix F

F.1. Decomposition Results for the two commitment periods

LMDI Results First Commitment Period (08-12)				
D_{act}	0,994217		Agriculture	0,9968918
D_{str}	0,950695		Industry	0,9106802
D_{int}	0,928416		Energy	0,9768172
D_{pop}	1,0383237		Services	1,0022376
D_{eint}	0,9460292		Transport	0,969833
D_{tot}	0,8619901		Residential	1,0000171

LMDI Results Second Commitment Period (13-18)				
D_{act}	1,05683		Agriculture	1,0130256
D_{str}	0,9336218		Industry	1,0028831
D_{int}	1,0263779		Energy	0,9772148
D_{pop}	1,0291313		Services	0,9915325
D_{eint}	0,9406085		Transport	0,9954299
D_{tot}	0,9803093		Residential	1,0004253