POLITECNICO DI TORINO

Master's Degree in **Architecture Construction City**

Master's Degree Thesis

URBAN SCALING OF MUNICIPALITIES IN THE NETHERLANDS: RELATIONSHIP BETWEEN CO_2 EMISSIONS AND POPULATION SIZE

Supervisor
Prof. Luca D'Acci

Candidate
Ecem Şenkal

September 2021

ACKNOWLEDGEMENTS

*First and foremost, I would like to express my sincere gratitude to my supervisor **Prof. Luca D'Acci** for his guidance and feedback throughout this dissertation. I would also like to give a special thanks to **my beloved family** as a whole for their love, unconditional support, and emphaty, especially to my nephew **Pamir,** for bringing me joy even in the most stressful moments. Last but not least, I am deeply grateful to **my friends** for sharing their moral support, as well as to my boyfriend, **Berkay** for his constant encouragement and willingness to help.*

ABSTRACT

Given the unquestionable urgency of predictive and quantitative urban organization theory and sustainable development, this dissertation aims to identify the power-law relationship between CO_2 emissions and city size in terms of population in the Netherlands. The multiple regression analysis was conducted with cross-sectional data with respect to the year 2018. The results indicated a significant association between population size, income per capita, and carbon dioxide emissions in the Netherlands. The analysis revealed a nearly linear scaling behavior, with a 1 percent increase in population size associated with a 1.03 percent increase in CO_2 emissions. It is also observed that there is a negative relationship between income per capita and CO_2 emissions. The results do not display neither economies nor diseconomies of scale concerning population size and CO_2 emissions.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 Background

As a result of rapid urbanization, climate change is accelerating the intensity of many of the consequences that are already present, towards the planet and for human settlements throughout the world (UN-Habitat, 2011). As a primary cause of climate change on Earth (Dodman, 2011; Ribeiro et al., 2019), carbon dioxide emissions in cities are affected by a number of factors, including the local climate, urban form, population size, building density, technology, as well as average income or wealth (Mohajeri, 2015). Several studies have addressed the strong relationship between city size and carbon dioxide emissions (Fragkias et al., 2013; Gudipudi et al., 2016; Oliveira et al., 2014). Therefore, understanding how the size of a city influences emissions can provide insight into how the size of a city might be used as part of a bigger regional or national strategy to reduce emissions (Fragkias, 2013).

This dissertation proposes to contribute to the empirical literature on the urban scaling -power-law relation between carbon dioxide emissions and city population- in the case of the Netherlands. Moreover, the relationship between carbon dioxide emissions and average annual personal income, average household natural gas consumption, and average household electricity consumption will also be examined as control variables.

1.2 Problem Statement

While rapid urbanization has driven innovation and socioeconomic growth, it has also resulted in several global issues, ranging from climate change and its implications for food, energy, water supply, public health, and the global economy (Bettencourt et al., 2010; Gudipudi et al., 2016). Despite occupying just 0.4-0.9 percent of the world's land surface, cities are responsible for more than 70% of emissions (Reckien et al., 2007; Ribeiro et al., 2019). CO_2 emissions from urban consumption, both direct and indirect, have dominated global overall CO_2 emissions, and rapidly rising urban CO_2 emissions are one of the major factors for the rapid rise in global CO_2 emissions (Cai et al., 2013; Dhakal, 2009; IEA, 2009; Satterthwaite, 2008; UN-Habitat, 2011). As a consequence, one of the major issues of the present is the sustainable management of urban areas across the world.

In addition to the previously addressed issue of rapid urbanization and rising carbon dioxide emissions, another issue is that existing literature debates the scaling behavior of carbon dioxide emissions and city size, and produces conflicting results. Some studies reveal sublinear relationships, whereas others demonstrate superlinear relationships. However, this research aims to indicate whether which of these scaling behaviors is valid for the Netherlands.

As it is pointed out by Bettencourt, the properties of contemporary urban systems in Europe are less studied than in other nations (2016). Likewise, literature on urban scaling is concentrated more on the United States, the United Kingdom, and China, while few studies conducted on European countries can be found. The empirical research on cities in the Netherlands seeks to contribute to the literature on urban scaling in European countries.

1.3 Research Questions and Objectives

What is the relationship between carbon dioxide emissions and the city size in terms of population in the Netherlands?

While answering this research question, following objectives will be evaluated;

- To conduct a linear regression analysis, with relevant data of the Netherlands,
- To observe the relationship between carbon dioxide emissions and other independent variables,
- To compare the linear regression analysis from this study with the existing literature.

1.4 Overview

The first chapter provides an overview of the dissertation's background, problem statement, research questions, and objectives. The introduction chapter, as Chapter 2, is followed by background information on scaling, urban scaling, and multiple linear regression, which is the analysis method used in this research. Various studies from the relevant literature will be given in Chapter 3. Specifically, studies that result in different scaling behaviors will be introduced. Chapter 4 describes the data and methods used in the study, then the results and discussion will be indicated in Chapter 5. Chapter 5 will also identify limitations of the research. Finally, Chapter 6 outlines the conclusions of the analysis.

CHAPTER 2: BACKGROUND

2.1 Scaling/Allometry

Scaling, or in other words, allometry, is an analytical framework that represents the relationship between properties of systems and measures of their sizes (Bettencourt et al., 2020). Starting with biology, scaling successfully validates that size alone (body mass) provides satisfactory information to predict many characteristics, such as an animal's lifespan, metabolism, and heart rate (Arcaute et al., 2013). It is noteworthy that these characteristics of biological organisms and more scale with body mass, M, as a power law. The exponent of the power law is typically a multiple of 1/4 which is expressed as 1/(d + 1) and d is the dimension. In order to clarify, if the metabolic rate, which is the power required to sustain the organism, B, scales as $B \propto M^{3/4}$, metabolic rate per unit mass decreases with body size as $B/M \propto M^{-1/4}$. Thus, this relationship fundamentally indicates that larger organisms consume less energy per unit time and per unit mass. Furthermore, in terms of almost all biological rates, times, and internal structure, the existence of such universal scaling laws may lead to the conclusion that mammals are scaled versions of one another and all scaled in a nonlinear, predictable way. For example, a gorilla is a scaled version of a mouse, an elephant is a scaled version of a gorilla, and so on (Bettencourt et al., 2007). Although scaling was originally introduced in the context of evolutionary theory to describe the correlation between relative dimensions of parts of body size (Oliveira et al., 2014), the use of scaling analysis as a method to reveal basic dynamics and structure has great importance for understanding problems across disciplines (Bettencourt et al., 2007, 2020). In recent decades, a perspective has emerged in disciplines as diverse as economics, geography, and complex systems -from equations of state for gases and liquids, to biological metabolism, to populations in ecology and anthropology, and to the properties of firms and cities- that proposes many properties of cities are quantitatively predictable due to agglomeration or scaling effects (Bettencourt et al., 2016, 2020).

2.2 Urban Scaling/Allometry

Cities are shaped by geographic, cultural, and political constraints as the result of complex social and economic dynamics (Arcaute et al., 2015). Therefore, each city has developed under unique geographical, political, and cultural aspects. Despite the heterogeneity of their historical development, certain characteristics that are common to all cities are recognizable regardless of their location, such as the fractality of cities, the Zipf distribution of city sizes, and population growth laws (Arcaute et al., 2013). In recent past, attempts to formalize these certain characteristics or assumptions mathematically have introduced the urban scaling hypothesis, which basically can be described as certain properties of all cities change with their size in a predictable scale-invariant way, on average (Bettencourt et al., 2013). The change in nonlinear properties of how cities work exhibits either sublinear behavior, meaning that quantities grow more slowly than city size, namely economies of scale, or superlinear behavior, meaning that quantities grow faster than city size, namely diseconomies of scale (Bettencourt et al., 2020). Consequently, as pointed out by sublunar or superlinear behavior, population city size alone as a characteristic of the urban system displays rates of innovation, income and employment, household electrical consumption, road surface area, and many others quantified by scaling laws. This quantitative understanding of human social organization and dynamics of cities that identifies urban scaling laws could be quite crucial to encourage managing current global challenges affecting cities, such as the impact of transport and industrial emissions on climate change, natural resource use, and the growth of urban poverty (Arcaute et al., 2013; Bettencourt et al., 2020).

2.3 Formalizing of Urban Scaling

Any average functional quantity is the urban scaling's requirement, which is Y as a scale invariant. The statement represents that

$$Y(\lambda N)/Y(N) = f(\lambda),$$

where the function f(λ) does not depend on N, which is the population size, but does depend on the arbitrary relative population size, $\lambda > 0$. Despite the fact that this statement has not always been identified in a way that is a scaling relation, it has been adopted frequently for different disciplines. Likewise, based on many empirical studies, power law scaling relations are described mathematically

$$Y(N)=Y_0\, N^{\beta},$$

as by verifying direct substitution (Arcaute et al., 2013; Bettencourt et al., 2007, 2013; Molinero et al., 2019). The scale of Y can be determined by the constants in N, Y_0 and β. Specifically, the scale of Y can be explained as $Y_0 = Y\ (N = 1)$, and the relative increase in the rate of Y in terms of the rate of N , that is $\beta = d_t \ln(Y)/d_t \ln(N)$. Y can either stand for energy or infrastructure sources, wealth, patents, pollution, and more. Along with that, Y_0 is normalization constant that is depends on time and differs from the subjected urban system. The exponent β is time-independent or slightly varying and display general dynamic rules. In particular urban systems, similar quantities displays similar exponent, β, values (Bettencourt et al., 2007, 2013).

2.4 Regression Analysis

Regression is a statistical method that aims to analyze the relationship between variables. In most cases, the researcher is looking for the causal effect of one variable on another (Sykes, 1992). The variable of interest that is defined by the mathematical expressions is called the dependent variable and symbolized by *y*. As predictor or explanatory variables, other variables which are expected to provide information on the behavior of the dependent variable are included in the model. These variables are referred to as independent variables and are represented by *x* (Dickey, 1998).

2.4.1 Multiple Regression Analysis

Multiple regression is a technique that allows additional aspects to enter the analysis separately in order to evaluate each of their effects. It's useful for estimating the impact of various effects on a single dependent variable (Sykes, 1992). Above all, the dependent variable y may be associated with a number of *k* independent or regressor variables which are referred as *x* (Montgomery, 2003). Multiple regression model is described by the given equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u.$$

The parameters β_j, j=0, 1…k, are called the regression coefficients. It indicates the linear dependence of the dependent variable *y* from the independent variable *x*. β_0 is the constant term, which has the value of y when x is 0. The random variable *u* expresses the regression error and is described as the difference between the actual value of *y* and the predicted value of *y* (Montgomery, 2003).

2.5 OLS (Ordinary Least Squares) Assumptions

As it is discussed by Osborne et al., the majority of statistical tests are based on particular assumptions about the variables used. If these assumptions are not met, the outcomes may not be reliable (2002). Thus, OLS assumptions must be held true to confirm that the multiple regression model is the best linear unbiased estimator.

2.5.1 Linearity

The linearity assumption refers that the regression model is linear in the coefficients and the error term. The relationship between dependent and independent variables can only be properly estimated using standard multiple regression if the relationships are linear in nature. The regression analysis results will miscalculate the true relationship if the relationship is not linear (Osborne, 2002).

2.5.2 Random Sampling

The dataset used to estimate the regression model must have been randomly sampled from the population (Wooldridge, 2006). Because, there is a risk of introducing an unknown factor into the analysis if the sample is not random. Random sampling assumption also refers to the sample size, in other words, the observations, for the regression model should be larger than the number of parameters to be estimated.

2.5.3 Conditional Mean Zero

The error term accounts for the variation in the dependent variable that the independent variables do not explain. The estimates that are generated from the model are unbiased and consistent if the error term for each observation, u, is drawn from a distribution that has a mean of zero, or in other words, the expected value of the error (Sykes, 1993).

2.5.4 No Perfect Collinearity

There should be no exact linear relationships, namely correlations among the independent variables. The high level of correlation between several independent variables is called multicollinearity (Woolridge, 2006). Although multicollinearity of a moderate degree may not be considered as a problem, drastic multicollinearity can enhance coefficient estimate variance and cause them to be extremely sensitive to slight model modifications (Frost, 2013).

2.5.5 Homoscedasticity

The error variance must be the same across all levels of the independent variables. This situation is known as homoscedasticity. When the heteroscedasticity is high, the results of the analysis can be skewed significantly (Osborne, 2002). The assumption of homoscedasticity is fulfilled to determine model efficiency (Wooldridge, 2006).

2.6 The New Science of Cities

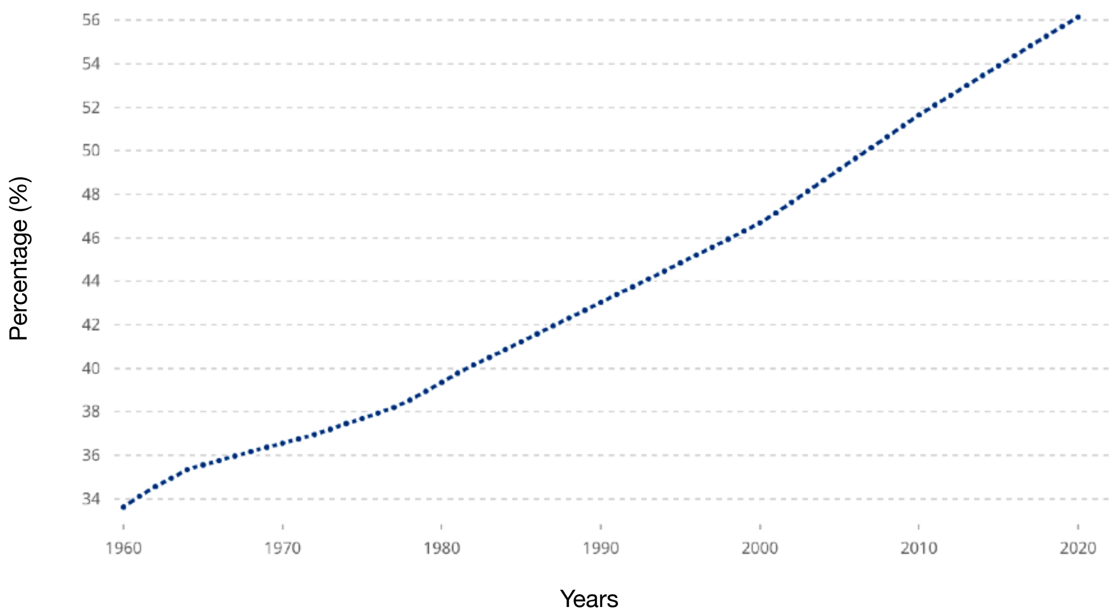
Collecting and sharing data availability has started to grow with acceleration in recent past, and it provides crucial characteristics of cities, such as statistical patterns of land use, urban infrastructure, and rates of socioeconomic activity. Currently, improved and extended data availability is leading quantitative studies of urban systems to open the way to the new Science of Cities (Bettencourt, 2013; Bettencourt et al., 2013; Louf et al., 2014a, 2014b). This science has the capacity to unite competing paradigms in the study of cities, enrich prevailing theories of city planning, and allow city planners to produce operational tools that lead to realistic city plans that will improve city dwellers' way of living. It provides awareness of the city's resource limits on urban density, sprawl and sustainability issues (Batty, 2008). To put it simply, depending on the scaling exponents, assuming that a city is predicted to double in size over the next decades, dozens of performance indicators, growth rates, infrastructure costs, etc. can be derived and proactively used in urban planning. Scaling laws offer apparent constraints on urban performance indicators and an opportunity to change at a particular level of growth (Molinero et al., 2019). Especially on the basis of the global urbanization that the world is facing currently, there is an undeniable urgency to predictive and quantitative urban organization theory and sustainable development. In light of the new Science of Cities, quantitative understanding of human social organization and dynamics in cities is a significant step directing progress towards sustainability (Batty, 2008; Bettencourt et al., 2007).

CHAPTER 3: LITERATURE REVIEW

3.1 Urbanization and Climate Change

Between 1950 and 2018, the world's urban population more than quadrupled, from 0.8 billion to 4.2 billion citizens. As a result, the world's population became increasingly urbanized between 1950 and 2018, with the percentage of people living in cities increasing from 30% in 1950 to 55% in 2018. Considering this accelerated urbanization, the world's population shifted for the very first time in 2007 from rural to urban. (Figure 3.1 demonstrates the global urban population, while Figure 3.2 demonstrates the Dutch urban population.) The urbanization trend is projected to continue for decades, with an ever-increasing percentage of the world's population living in cities. The world's urban population is projected to hit 5 billion in 2028 and 6 billion in 2041, indicating that urbanization will continue to grow. These patterns in urban and rural population growth rates, as well as the subsequent urban-rural population distribution, would undoubtedly

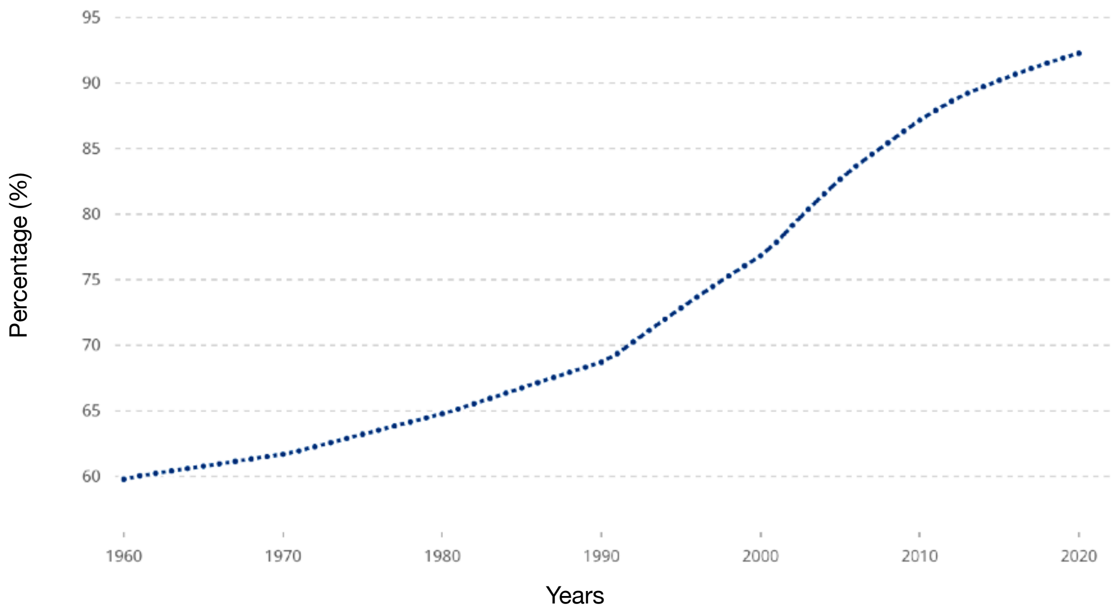
Figure 3.1. Urban Population of the World (% of total population),1960-2020



Urban population refers to people living in urban areas as defined by national statistical offices. Percentages are the numbers of persons residing in an area defined as ''urban'' per 100 total population.
Source: *United Nations Population Division. World Urbanization Prospects: 2018 Revision.*

have profound consequences for the global economy, the environmental quality, and the kinds of lives that people will lead (United Nations, 2019).

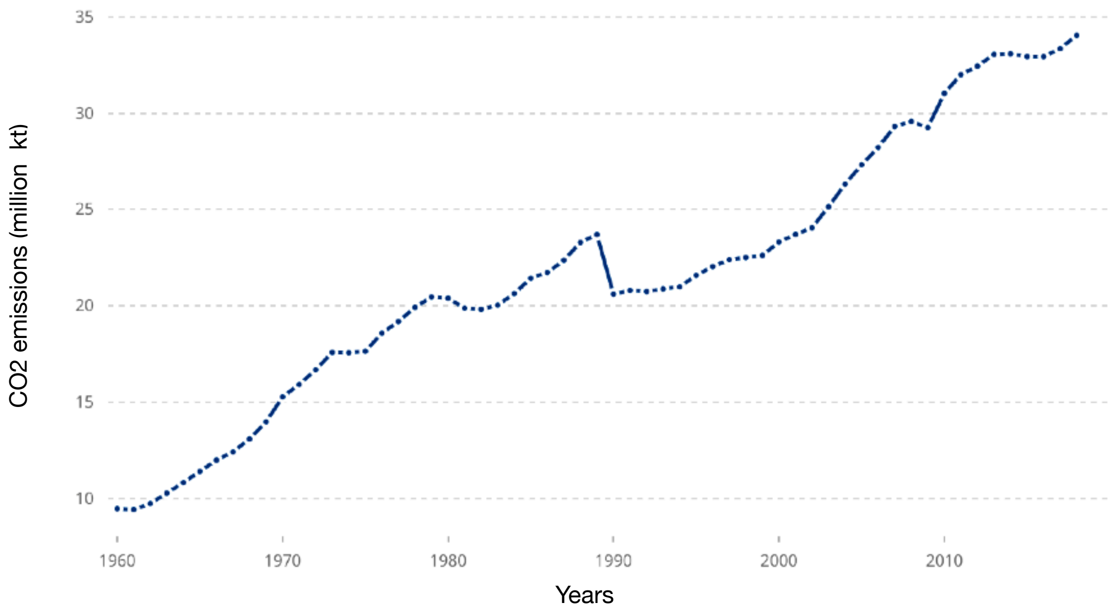
Figure 3.2. Urban Population of the Netherlands (% of total population),1960-2020



Urban population refers to people living in urban areas as defined by national statistical offices. Percentages are the numbers of persons residing in an area defined as ''urban'' per 100 total population.
Source: *United Nations Population Division. World Urbanization Prospects: 2018 Revision.*

As a result of rapid urbanization, climate change is accelerating the intensity of many of the consequences that are already present on the planet and for human settlements throughout the world (UN-Habitat, 2011). Carbon dioxide emissions are one of the primary causes of climate change on Earth (Dodman, 2011; Ribeiro et al., 2019). Despite occupying just 0.4-0.9 percent of the world's land surface, cities are responsible for more than 70% of emissions (Reckien et al., 2007; Ribeiro et al., 2019). Increasing global CO_2 emissions are shown in Figure 3.3 between the years 1960 and 2018. The main source of atmospheric CO_2 comes from the burning of fossil fuels. This fossil-fuel energy is used in transportation, building heating and cooling, and the manufacture of cement and other products, all of which are major activities in cities (UN-Habitat, 2011). Urban dwellers consume more per capita than rural dwellers (United Nations, 2019). Higher energy demands, related to higher living standards, such as higher income, smaller households, bigger flats and houses, more spare time relative to working hours, changing economic mechanisms such as globalization, specialization in products and human labour, and a general rise in people's traffic radius, as well as exchange rates of goods and services, all contribute to the increased use of fossil fuels (Reckien et al., 2007). However, another perspective is that cities have the advantage of economies of scale (Fragkias et al., 2013). As such, due to their mass transportation systems, polycentric and dispersed cities may generate more pollution than compact and monocentric cities (Gaigné et al., 2012).

Figure 3.3. Carbon Dioxide Emissions of the World (kt), 1960-2018



Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement.
Source: *Data for up to 1990 are sourced from Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory, Tennessee, United States. Data from 1990 are CAIT data: Climate Watch. 2020. GHG Emissions. Washington, DC: World Resources Institute. Available at: climatewatchdata.org/ghg-emissions.*

3.2 CO_2 Emissions and City Size Relationship

The role of urbanization in rising carbon dioxide emissions has primarily been studied by using scaling relationships or by focusing on the understanding of how population density affects CO_2 emissions per capita (Ribeiro et al., 2019). The previous studies using the scaling hypothesis have investigated the relationship between city size, population density and CO_2 emissions (Fragkias et al., 2013; Glaeser et al., 2010; Gudipudi et al., 2016; Oliveira et al., 2014), as well as the relationship between city size, urban form, transport related energy consumption and CO_2 emissions (Gudipudi et al., 2016; Louf et al., 2014b; Mohajeri et al., 2015), also explored CO_2 emissions in polycentric versus monocentric cities and their compactness and complexity (Makido et al., 2012).

Figure 3.4. Cross-sectional log-log regressions for years (A) 1999 and (B) 2008

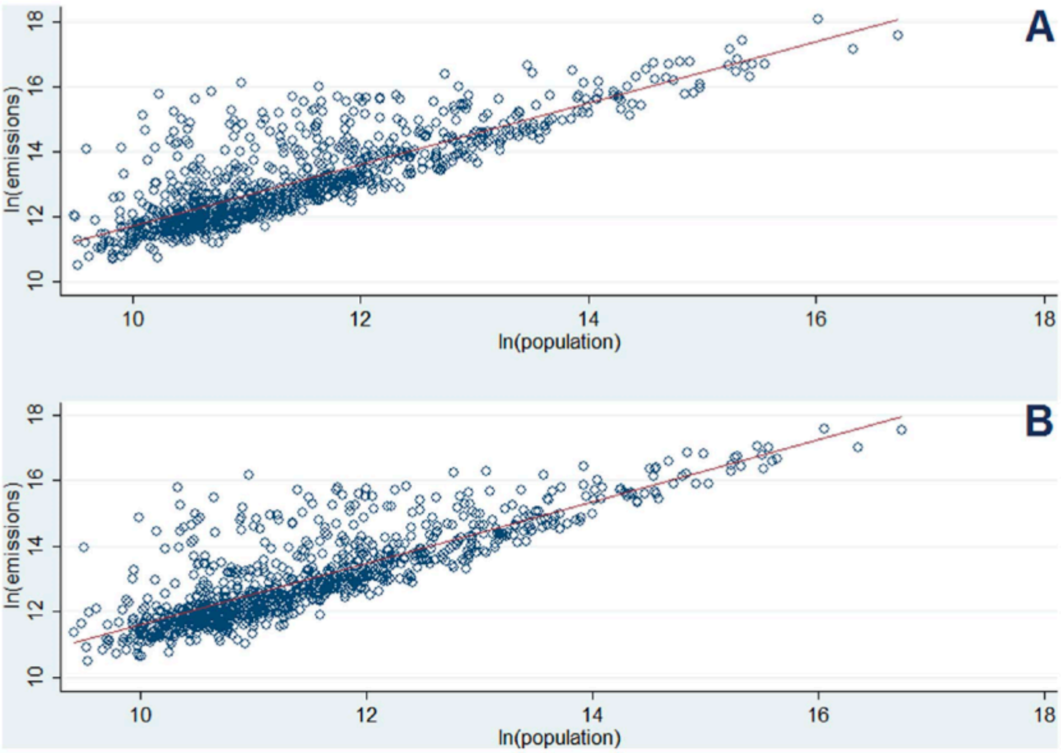
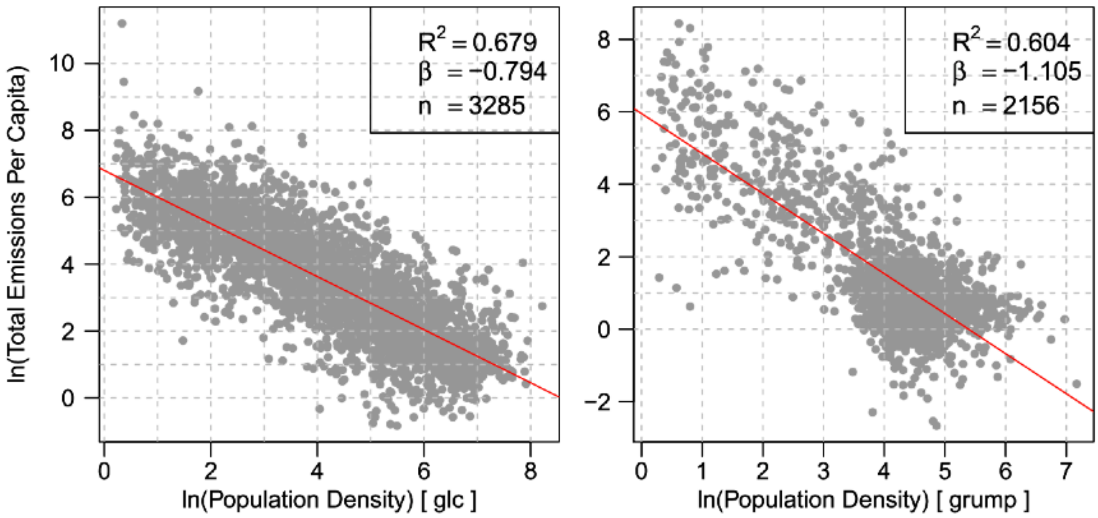


Figure 1.4. demonstrates the cross-sectional regression results in two different years. Fragkias et al. (2013) present slightly sublinear relationship between city size and CO_2 emissions for large metropolitan areas of the United States, using administrative boundaries.
Source: *doi:10.1371/journal.pone.0064727.g001*

Several studies differ significantly based on their findings. Some research, for example, concludes that larger cities are not more efficient than smaller ones (Makido et al., 2012; Fragkias et al., 2013; Louf et al., 2014b; Mohajeri et al., 2015; Oliveira et al., 2014). Using administrative boundaries to define the area of cities, Fragkias et al. (2013) propose a linear relationship between city size and carbon dioxide emissions for large metropolitan areas in the United States. Initially, Fragkias et al. (2013) showed that a 1 percent increase in population size is associated with a 0.93 percent increase in CO2 emissions in 2008. The population size coefficient shifts to 1.028 when a measure of population density and per capita personal income are included as control variables, indicating a fairly proportional effect for the same year. Figure 3.4 demonstrates the scaling behavior with a coefficient of 0.93, whereas the first graph refers to 1999 and the second graph refers to 2008. Additionally, despite drawing the same conclusion that larger cities are not more efficient, Oliveira et al. (2014) reveal two distinct findings as a result of using different boundary definitions. While the City Clustering Algorithm (CCA) shows a superlinear scaling behavior (β=1.46) between CO_2 emissions and the city population, the administrative boundaries (MSA) show a sublinear relationship between the two across all US cities. Furthermore, another research based on the findings of fifty Japanese cities by Makido et al. (2012) indicates that residential CO_2 emissions per capita were negatively correlated with income and positively correlated with city size, whereas transport related CO_2 emissions per capita were positively correlated with population density and compact and mono-centric settlement types. In contrast, Gudipudi et al. (2016) identifies a sublinear relationship between population density and total emissions, which includes both on road and building emissions on a per capita basis, as can be seen in Figure 3.5. The sublinear relationship is derived from the City Clustering Algorithm (CCA) and utilizes the gridded CO_2 emissions data of all populated areas in the United States. As a consequence, with growing population density, emissions per capita tend to decrease. Another study that aims to demonstrate carbon dioxide emissions related to new construction in multiple locations around the United States came to a similar conclusion. As stated by Glaeser et al. (2009), cities have considerably reduced emissions than the suburbs. Along with that, more populated cities have lower emissions, considering emissions from driving, public transportation, house heating, and household electricity use.

Moreover, variations in outcomes can be found in previous studies that concentrate on fuel consumption, street network, congestion, and CO_2 emissions. Despite polycentrism, diseconomies associated with congestion scale superlinearly with population size, results by Louf et al. (2014b) imply that cities are unsustainable as a result of traffic sensitive transportation infrastructure. Thus, the quantity of CO_2 emitted per capita increases as the size of the city increases. In addition, according to Mohajeri et al. (2015), the street network in a large city is more efficient compared to a small city, considering sublinear relationships between the number of streets, total length of streets, area covered by the street network and city size. Mohajeri et al. (2015), on the other hand, found that fuel consumption and CO_2 emissions have a linear relationship with city size and a superlinear relationship with total street length, taking into account that a greater portion of the street network in a large city is used at near-full capacity for a longer period of time than in a small city. In that case, large cities are likely to be less energy efficient and less sustainable than smaller ones.

Figure 3.5. Relationship between population density and CO_2 efficiency at 5 km threshold distance for GLC (left) and GRUMP (right) data on a natural logarithmic scale



Gudipudi et al. (2016) identifies a sublinear relationship between population density and the total emissions (i.e. the sum of on-road and building emissions) on a per capita basis in inhabited areas in the US. Figure 1.5. shows distinct results from two different datasets.
Source: *doi.org/10.1016/j.enpol.2016.01.015*

CHAPTER 4: METHODOLOGY

4.1 Introduction

The research is conducted in order to determine primarily the relationship between carbon dioxide emissions and the city size in terms of population in the Netherlands. As a quantitative research method, multiple regression analysis is adopted with a cross-sectional data respect to year 2018. A descriptive dataset is used without intervening.

4.2 Data

4.2.1 The Source and Units of Data

The source of the population size, average personal income, average household natural gas consumption, average household electricity consumption data and the definitions of the urban agglomerations is the Netherlands Central Bureau of Statistics (CBS). CO2 emissions data is provided by the Emission Register Project of the Netherlands, which is in co-operation with. The data was obtained according to municipal redivisions.

The CO_2 emissions of each municipality are defined by the unit of kilograms concerning total CO_2 emissions to the air. The income per capita data is described yearly and the unit is 1000 euros. It includes the total of income from employment, income from own business, insurance benefits and social security benefits (with the exception of child benefits and child-related budget). The average household natural gas consumption data has a unit of m^3 and the average household electricity consumption data has a unit of kWh. The data provides regional data by municipalities. The population size is obtained by regional totals respecting the administrative boundaries of municipalities. Lastly, the entire data used in multiple regression analysis is in reference to the year of 2018.

As specified previously, personal income, natural gas consumption, and electricity consumption data is adopted as average values. Although using data that consists of total amounts increases the R square, therefore the reliability of the model, average values are used instead of total amounts. The reason is that using total amounts also increased correlation between independent variables considering a small amount of increase in R square of the model.

4.2.2 Administrative Divisions of the Netherlands

There are 12 provinces in the Netherlands, each with its own size and population. The province of Utrecht is the smallest geographically, and the province of Flevoland has the smallest population, however it is rapidly rising. Cities are defined as municipalities in the Netherlands. The municipalities, namely 'gemeenten', which are subdivisions of their respective provinces, are the Netherlands' second-level administrative division. Figure 4.1 shows provinces and municipalities of the Netherlands. A total of 380 municipalities form the Netherlands. Neighboring municipalities combined over time as some policy and service areas demanded more administrative-organizational strength, thus, the number of municipalities have decreased. This process is still in progress that hasn't reached a standstill yet. Amsterdam is the most populous municipality around 800,000 inhabitants. Schiermonnikoog which is one of the islands along the coast of the Netherlands, has the least number of inhabitants with only 900 inhabitants (The Association of Netherlands Municipalities, 2020).

4.2.3 Dataset

In total, 343 cities, namely municipalities have been used in this dissertation. Specifically, Het Hogeland, Westerkwartier, Noardeast-Fryslân, Meppel, West Betuwe, Vijfheerenlanden, Hoeksche Waard, Molenlanden, Alphen-Chaam, Altena, Beek, Beekdaelen, and Beesel are excluded from the study due to the absence of observations for each variables. The dataset includes variables of CO_2 emissions, population size, income per capita, natural gas consumption, and electricity consumption. Number of observations, standard deviations, minimum, maximum, and mean values of the dataset is indicated by the Table 4.2, Descriptive Statistics.

Figure 4.1. Provinces and Municipalities of the Netherlands

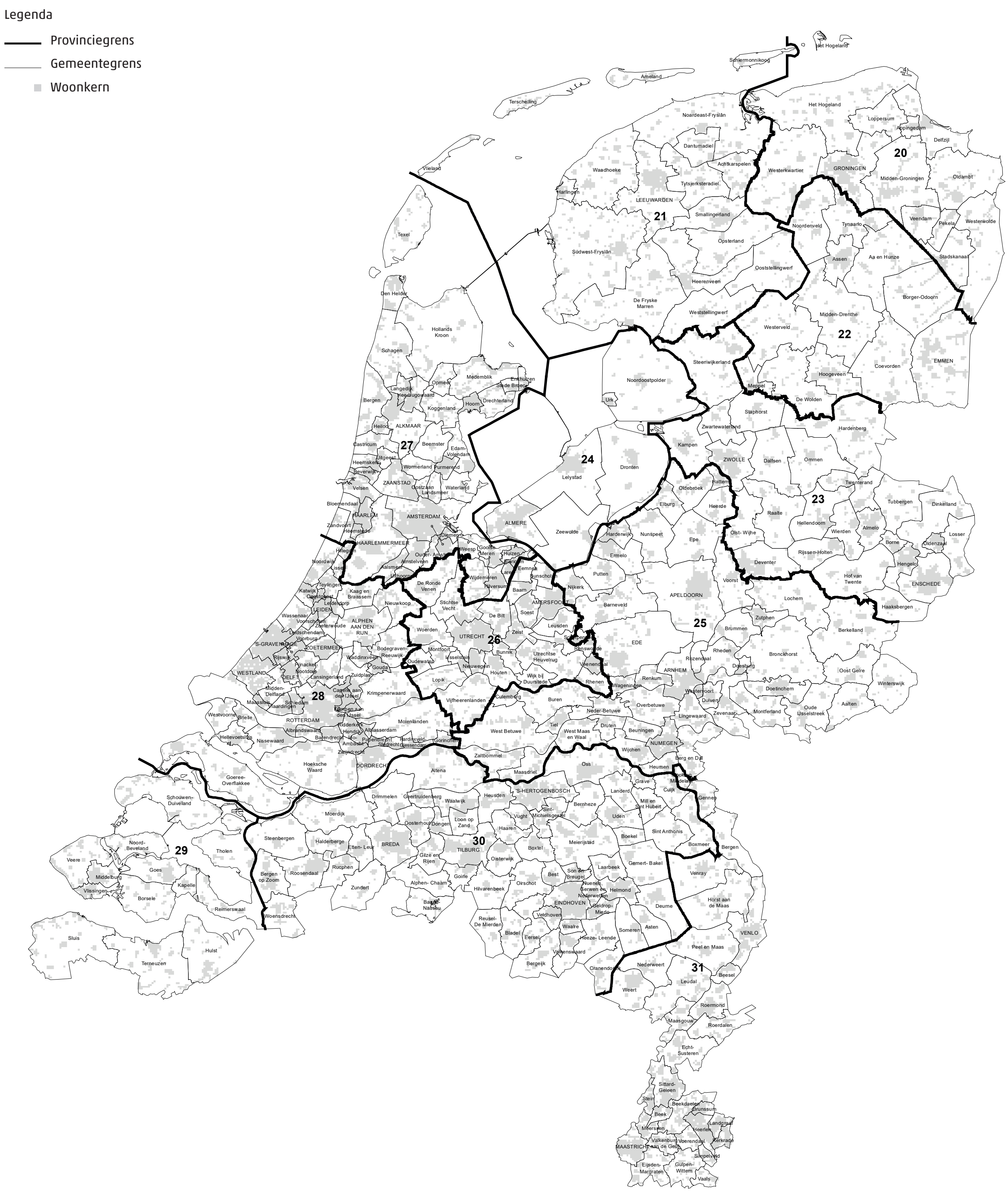


Figure 4.1 illustrates administrative boundaries of 12 provinces and 380 municipalities.
Source: *www.cbs.nl*

Table 4.1. Operationalization of Variables

Variable	Type	Abbreviation	Unit	Definition
Carbon dioxide emissions	Dependent variable	CO_2	kg	CO_2 emissions of each municipality is defined by total CO_2 emissions to the air from both stationary and mobile sources. Stationary sources include energy sector, industry, private households and other. Mobile sources include transportation.
Population size	Independent variable	pop	number of person s	Population size is defined in regional totals respected administrative boundaries of municipalities.
Income per capita	Independent variable	inc	1000 euros	Personal income includes the total of income from employment, own business, insurance benefits and social security benefits (with the exception of child benefit and child-related budget). Income insurance premiums (with the exception of national insurance premiums) have been excluded. The target population includes all private households with known income.
Household natural gas consumption	Independent variable	gas	m^3	Natural gas consumption is accounted as average annual consumption of natural gas from private homes. It is provided as regional data by municipalities. In the calculation of the average natural gas consumption, homes with very low or even zero consumption are included if there is district heating.
Household electricity consumption	Independent variable	el	kWh	Electricity consumption is accounted as average annual consumption of electricity from private homes. It is provided as regional data by municipalities.The own generation of electricity, for example with solar panels, is unknown and therefore not included in the average annual consumption. Collective consumption as lift installations or hall lighting are also not included in the calculation.

Table 4.2. Descriptive Statistics

Variable	Observations	Min	Max	Standard Deviation	Mean
Carbon dioxide emissions	343	6210590	30867700000	2041411899	460815336
Population size	343	936	862965	80103.92	50704.60
Income per capita	343	24900	56200	4352.03	32426.88
Natural gas consumption	343	370	2390	263.31	1438.44
Electricity consumption	343	2090	3900	340.28	3013.89

4.3 Analysis

4.3.1 The Model

The model has been used in order to estimate relationship between population size, income per capita, household natural gas consumption, household electricity consumption and CO_2 emissions of the municipalities of the Netherlands is multiple regression with logarithmic functions. This model is represented by the following equation:

$$log(CO2) = \beta_0 + \beta_1 . log(pop) + \beta_2 . log(inc) + \beta_3 . log(gas) + \beta_4 . log(el) + u. \quad (1)$$

The dependent variable in this equation is carbon dioxide emissions, and independent variables are population size, income per capita, household natural gas consumption, household electricity consumption consecutively.

4.3.2 OLS (Ordinary Least Squares) Assumptions

After the model is determined, in order to effectively utilize the capabilities of OLS, a set of assumptions must be met (Wooldridge, 2006). OLS assumptions and their definitions are indicated in the Background Chapter. Before applying the method of OLS to the relevant set of data specified previously and estimating the model, these assumptions will be satisfied; linearity, random sampling, conditional mean zero, no perfect collinearity and homoscedasticity. First, the linearity assumption should be met by examining residuals versus fitted values plot. Second, the random sampling assumption must be satisfied, whereas the dataset should not be intervened. Third, the residuals versus fitted values plot will be investigated once more to check if the assumption of conditional mean zero is held true. Next, a variance inflation factors (VIF) test will be performed to satisfy the no perfect collinearity assumption. Lastly, the homoscedasticity assumption must be met by reviewing the scale-location plot. Thus, when these assumptions hold true, the multiple regression model used in this dissertation will be the best linear unbiased estimator considering the relevant dataset. So that the regression analysis can produce reliable estimates.

4.3.3 Regression Analysis

The method of OLS is applied to estimate the multiple regression model. After conducting the regression analysis for the complete observations, model estimates are achieved. The complete observations imply Netherland's 343 municipalities and dataset including CO_2 emissions, population size, income per capita, natural gas consumption, and electricity consumption as variables for the year 2018. Further, the outliers of the dataset are detected. In order to detect outliers, the Residuals vs. Leverage plot is obtained. Then, by obtaining Cook's Distance Bar Chart, outliers are displayed as how strongly they influence the regression considering their Cook's distances. Outliers are observations that differ significantly from the overall pattern. Thus, excluding outliers from the data set would alter the regression results. Therefore, outliers are excluded from the regression analysis. Finally, regression analysis is also conducted without outliers and model estimates are presented once more.

4.3.4 Software

For the regression analysis conducted on this thesis, RStudio software is used with the support of the central processing unit (CPU). The CPU of the computer 1.4GHz

Quadcore Intel Core i5. As the process does not require much memory, graphical processing unit (GPU) is not used for the analysis. In constructing the algorithm of the thesis, some libraries of RStudio software are utilized. These libraries include *readxl, ggplot2* and *car* which helps to take raw input data from Microsoft Excel to RStudio, perform regression analysis and draw suitable graphical information to show the results of the analysis.

CHAPTER 5: RESULTS & DISCUSSION

5.1 The Model

The multiple regression model allows examining the influence of relevant independent variables on CO_2 emissions. As mentioned in the methodology section, the dissertation is focused on examining the relationship between CO_2 emissions and population size in cities, or to put it in a way that is classified as in the Netherlands, municipalities. In order to analyze the relationship, the model is illustrated as:

$$log(CO2) = \beta_0 + \beta_1 \,.\, log(pop) + \beta_2 \,.\, log(inc) + \beta_3 \,.\, log(gas) + \beta_4 \,.\, log(el) + u. \quad (1)$$

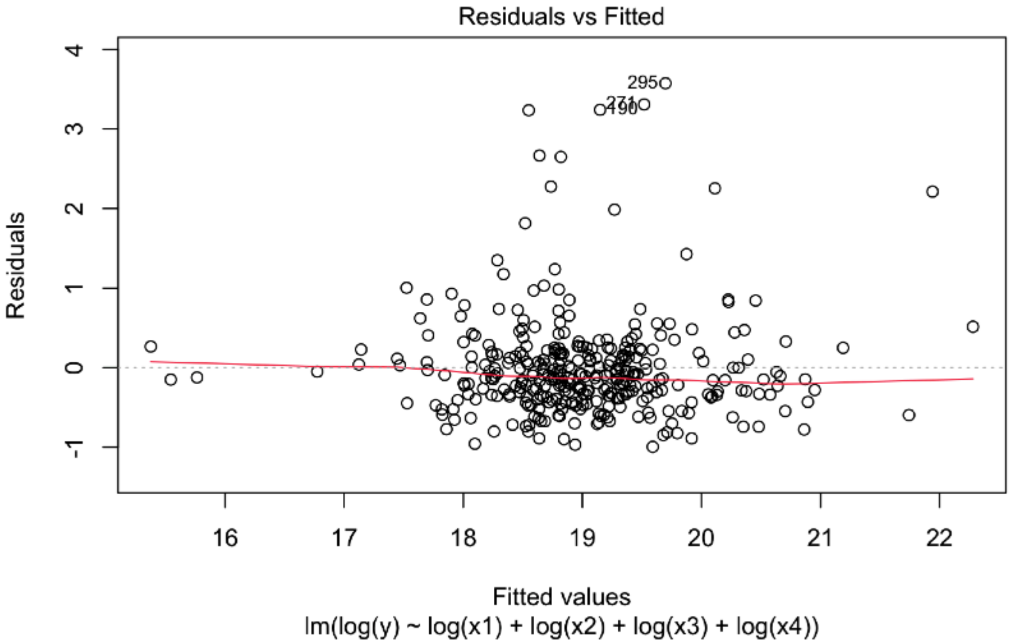
Carbon dioxide emissions are the dependent variable in this equation, whereas population size, income per capita, household natural gas consumption, and household electricity consumption are the independent variables.

5.2 OLS (Ordinary Least Squares) Assumptions

To obtain the best possible estimates from the model, the multiple regression model must satisfy certain assumptions that are also explained in Chapter 2: Background. The OLS estimators are unbiased under the first four Gauss-Markov assumptions, which are linearity, random sampling, no perfect collinearity, and zero conditional mean. As a consequence, including an irrelevant variable in a model has no effect on the unbiasedness of the intercept and other slope estimators. In addition, the first four were used to prove OLS' unbiasedness, while the fifth, homoscedasticity, was added to conclude that OLS is the best linear unbiased estimator (Wooldridge, 2006). The following are the steps to verify whether these assumptions hold true.

The first assumption to satisfy is ‘linearity’. In a more comprehensive meaning, the regression model is linear in the coefficients and the error term. The Residuals vs fitted plot shows the variability of the residual values with fitted values (predictor variables) as shown in Figure 5.1. An ideal plot should be symmetrically distributed and tend to cluster towards the middle of the plot. The more linear the relationship is, the better the predictive value is. In Figure 5.1, the red line which shows the average value of the residuals at each value of fitted value is nearly flat. Therefore, there is no distinct non-linear trend to the residuals. Although positive values for the residuals are slightly more prominent than negative ones, it does not violate overall symmetry and the cluster in the middle of the plot is distinguishable. As a result, the regression model is linear in the coefficients and the error term. Thus, the linearity assumption is satisfied.

Figure 5.1. Residuals vs Fitted Plot

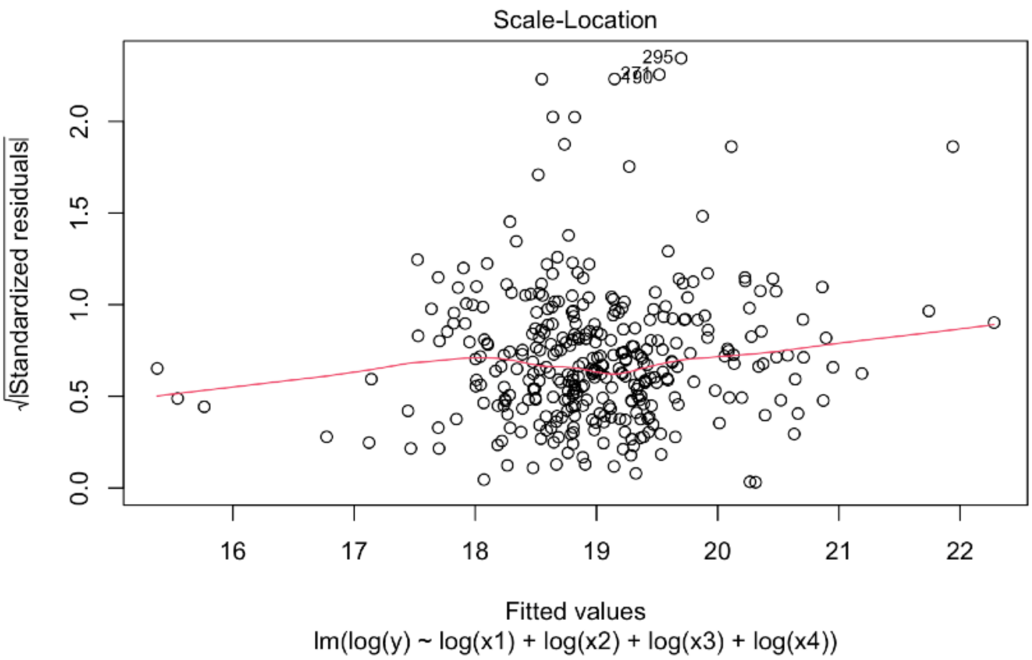


'y' indicates carbon dioxide emissions. 'x1', 'x2', 'x3', 'x4' demonstrate population size, income per capita, household natural gas consumption, household electricity consumption, consecutively.

Second, the 'random sampling' assumption needs to be fulfilled for the model to be unbiased. Essentially, the data must have been randomly sampled from the population. The collection of data is based on a full sample of the municipalities of the Netherlands. As it is explained in Chapter 4: Methodology, only 13 municipalities were excluded from the study due to lack of data. The remaining 343 municipalities are included without any selection in the dataset. Consequently, the random sampling assumption can be considered satisfied.

The third assumption is 'conditional mean zero'. In order to assume that the error term has a conditional mean of zero, the residuals versus fitted values plot should demonstrate a systematic deviations of symmetry around the horizontal line of zero. As it is also demonstrated in Figure 5.1, although there is no absolute symmetry between above and below the horizontal line zero, a distinctive asymmetry is not indicated by the plot. Residuals are clustered around the middle of the plot as an ideal residuals versus fitted values plot would demonstrate that it is also explained for the linearity assumption. No matter which value is chosen for the independent variables, the error term does not address a predictable error term. Consequently, the assumption that the error term has a conditional mean of zero is fulfilled.

Figure 5.2. Scale-Location Plot



'y' indicates carbon dioxide emissions. 'x1', 'x2', 'x3', 'x4' demonstrate population size, income per capita, household natural gas consumption, household electricity consumption, consecutively.

The next assumption to satisfy is ‘no perfect collinearity’, to put it another way, no independent variable is a perfect linear function of other explanatory variables. Multicollinearity occurs when one or more independent variable are a perfect linear function of other explanatory variables. In order to confirm that, variance inflation factors (VIF) test is performed. The numerical value of VIF expresses how much of the variance coefficient is being inflated due to multicollinearity. Considering, VIF test value 1 defines no correlation, and 5 defines moderate correlation. According to the test results, the test values are 1.281579, 1.060450, 1.480427, and 1.480301 for each independent variable. The model shows that there is an insignificant amount of correlation. Consequently, analysis shows that there is no multicollinearity. The fourth assumption is also met, thus, the model is unbiased.

The last assumption to satisfy and to confirm that the model produces the best linear unbiased estimates is ‘homoscedasticity’, or ‘ the error term has a constant variance’. The error variance must be the same across all levels of the independent variables, because uneven variances may result in biased and skewed results. The scale-location plot demonstrates the standardized values of the model would predict against standardized residuals obtained. As displayed in Figure 5.2, the red line is approximately horizontal. Then, the spread of the residuals is roughly equal at all fitted values. Also, there is no clear pattern among residuals, meaning that residuals are randomly distributed around the red line. Although the plot shows some outliers around the cluster, the outliers are not causing heteroscedasticity. Therefore, the assumption of homoscedasticity is satisfied for the multiple regression model.

The four Gauss-Markov assumptions (linearity, random sampling, no perfect collinearity, and zero conditional mean) are satisfied and unbiasedness is established. Then, assumption of homoscedasticity is also fulfilled to determine model efficiency. As a consequence, the multiple regression model is the best linear unbiased estimator.

5.3 Regression Analysis

The method of OLS is applied to estimate the multiple regression model. Based on the Netherland's 2018 data consist of 343 municipalities and the model developed as Equation (1), Table 5.1 presents the relevant multiple regression results. As it is demonstrated by the Table 5.1, the model is obtained the R-squared value of 0.6254 and adjusted R-squared value of 0.6210. When the exact model is conducted on the dataset with outliers removed, the outcome is shown in Table 5.3, with an R-squared value of 0.6237 and an adjusted R-squared value of 0.6192. Additionally, two of the variables which are household natural gas consumption and household electricity consumption are not statistically significant conforming to p-values of 0.09 and 0.52 respectively. In contrast, the population size and income per capita independent variables are statistically significant as it is indicated by the significance levels in Table 5.1 Further, coefficients of the variables will be interpreted in discussion part.

Table 5.1. Multiple Regression Results. Dependent variable: Carbon dioxide Emissions

Independent Variables	
Intercept	12.13** (3.89)
log(pop)	1.03*** (0.05)
log(inc)	-0.75* (0.30)
log(gas)	0.27 (0.21)
log(el)	0.25 (0.38)
Observations	**343**
R-squared	**0.6254**
Adjusted R-squared	**0.6210**

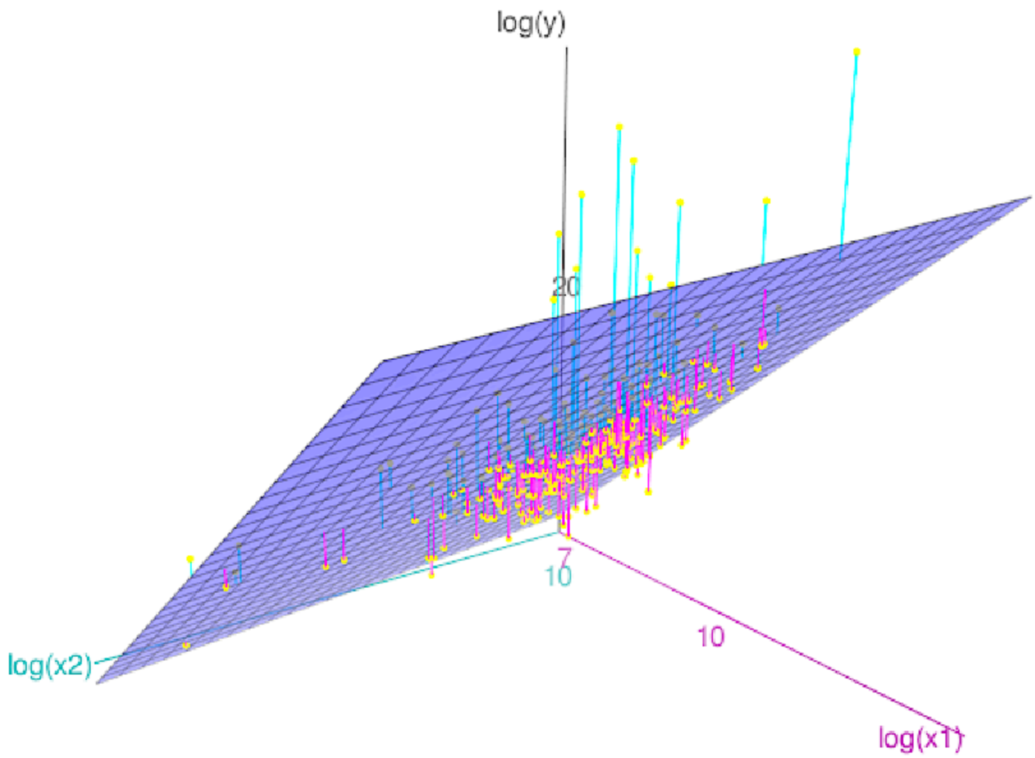
*Note: Standard errors are reported in parentheses. *, **, *** indicates significance levels. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.*

Table 5.2. Analysis of Variance, Dependent variable: log(CO2)

	Df	Sum Sq	Mean Sq	F-value	p-value
log(pop)	1	236.43	236.43	555.37	< 2e-16 ***
log(inc)	1	2.39	2.39	5.61	0.02 *
log(gas)	1	1.24	1.24	2.92	0.09 .
log(el)	1	0.18	0.18	0.42	0.52
Residuals	338	143.89	0.43		

** p < 0.05. ** p < 0.01. *** p < 0.001.*
Df: degree of freedom, Sum Sq: sum of square, Mean Sq: mean square.

Figure 5.3 3d Scatter Plot

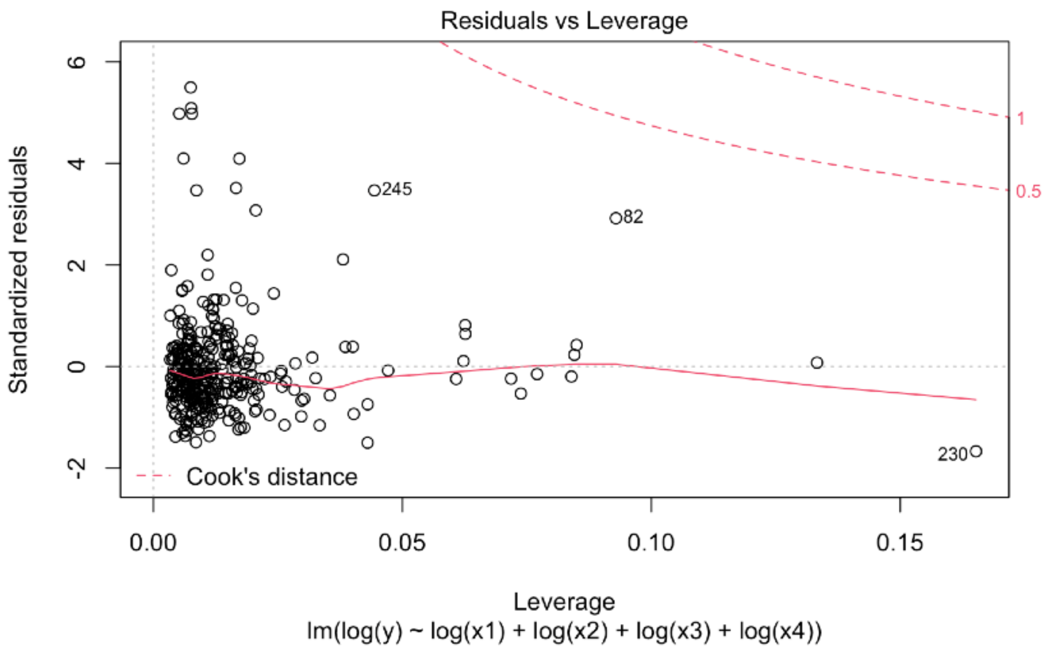


'y' indicates carbon dioxide emissions. 'log(x1)' demonstrates population size and 'log(x2)' demonstrates income per capita which are the two statistically significant independent variables.

5.4 Outliers

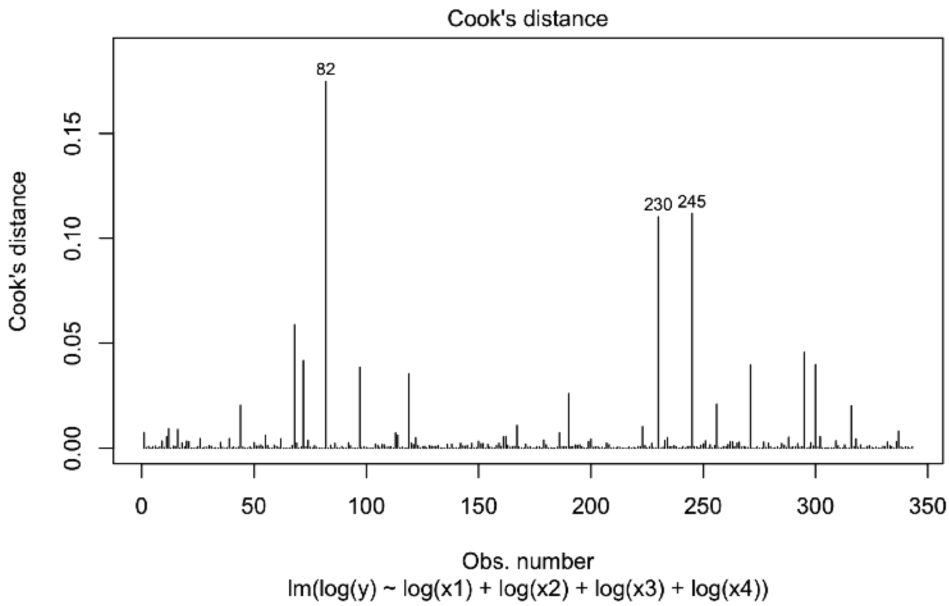
Outliers are observations in which the observed dependent value deviates from the overall trend given the independent value. If the residual for that observation is large, it influences the line and draws the line towards itself. The high-leverage observation will pull the regression line towards it. Figure 5.4 demonstrates the 'Residuals vs. Leverage' plot, Cook's distance is also indicated. Although Figure 5.4 displays the outliers, it is evident from Figure 5.5, which is a Cook's bar chart, the outliers are observations with the numbers 82, 230, and 245. These outliers are the cities (municipalities) of Druten, Pijnacker-Nootdorp, and Roosendal. Excluding outliers from the data set would alter the regression results. Therefore, regression analysis is also conducted without the outliers. Multiple regression analysis without outliers is resulted as Table 5.3. Coefficients of population size, income per capita and natural gas consumption remained constant. Coefficients of intercept is slightly increased from 12.13 to 12.20 and electricity consumption is slightly decreased from 0.25 to 0.24. Furthermore, a hardly noticeable change is also occurred in R-squared and adjusted R-squared. Table 5.5 reveals variations in the model evaluation of both model with and without outliers.

Figure 5.4. Residuals vs Leverage plot



'y' indicates carbon dioxide emissions. 'x1', 'x2', 'x3', 'x4' demonstrate population size, income per capita, household natural gas consumption, household electricity consumption, consecutively.

Figure 5.5. Cook's Distance Bar Chart



'y' indicates carbon dioxide emissions. 'x1', 'x2', 'x3', 'x4' demonstrate population size, income per capita, household natural gas consumption, household electricity consumption, consecutively.

Table 5.3. Multiple Regression Results without outliers. Dependent variable: Carbon dioxide Emissions

Independent Variables	
Intercept	12.20** (3.91)
log(pop)	1.03*** (0.05)
log(inc)	-0.75* (0.30)
log(gas)	0.27 (0.21)
log(el)	0.24 (0.39)
Observations	**340**
R-squared	**0.6237**
Adjusted R-squared	**0.6192**

*Note: Standard errors are reported in parentheses. *, **, *** indicates significance levels. * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.*

Table 5.4. Analysis of Variance without outliers, Dependent variable: log(CO2)

	Df	Sum Sq	Mean Sq	F-value	p-value
log(pop)	1	236.92	236.92	546.40	< 2e-16 ***
log(inc)	1	2.36	2.36	5.50	0.02 *
log(gas)	1	1.24	1.24	2.89	0.09 .
log(el)	1	0.16	0.16	0.39	0.53
Residuals	338	143.64	0.43		

** p < 0.05. ** p < 0.01. *** p < 0.001.*
Df: degree of freedom, Sum Sq: sum of square, Mean Sq: mean square.

Table 5.5. Model Evaluation

	Residual standard error	Multiple R-squared	Adjusted R-squared	F-statistic	p-value
Model (1)	0.6525	0.6254	0.6210	141.1	< 2.2e-16
Model (2)	0.6548	0.6237	0.6192	138.8	< 2.2e-16

Model (1) substitutes the model with the outliers, model (2) substitutes the model without the outliers.

In order to prevent the effect of observations that inconsistent with the dataset, outliers are eliminated. After eliminating the outliers, the model is determined as following equation:

$$log(CO2) = 12.20 + 1.03.log(pop) - 0.75.log(inc) + 0.27log(gas) + 0.24log(el) + u. \quad (2)$$

(3.91) (0.05) (0.30) (0.21) (0.39)

Dependent and independent variables are the same as explained in the previous equation: Carbon dioxide emissions are the dependent variable in this equation, whereas population size, average yearly personal income, average household natural gas consumption, and average household electricity consumption are the independent variables.

5.5 Preliminary Model & Discussion of Functional Form

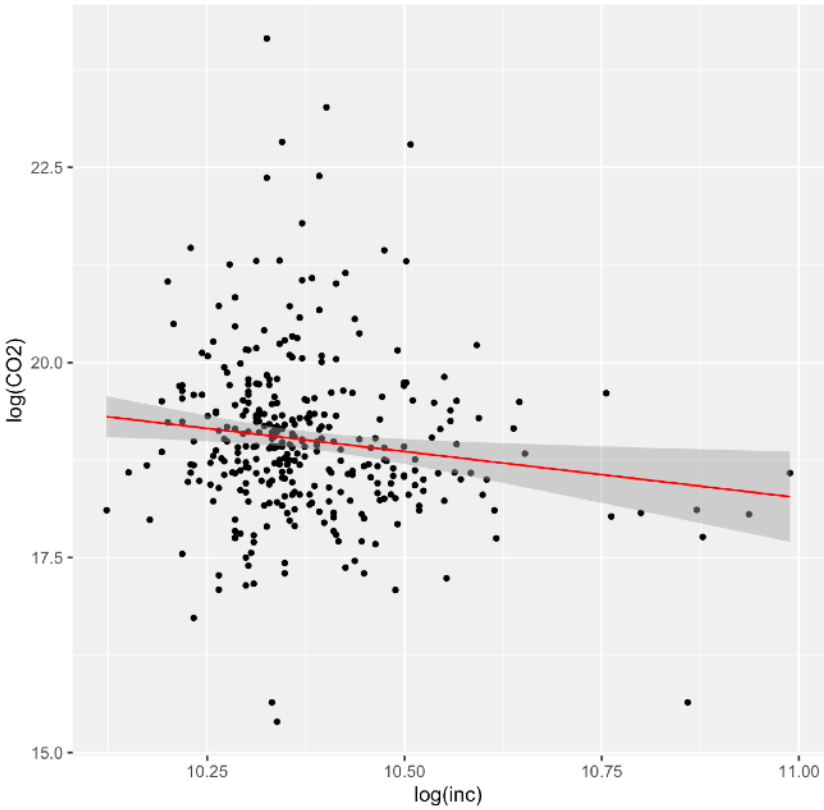
As a preliminary analysis, multiple regression has been performed by following the same procedure as discussed previously without logarithmic functions. However, the preliminary model could only explain 41% of the data. Therefore, it was not sufficient to explain the relevant correlation between independent and dependent variables. In order to linearize the model, logarithms of both sides of the existing equation have been taken, and Equation (1) has been achieved as the model of the analysis. In a regression model, logarithmically transforming variables is a frequent approach to dealing with situations where the independent and dependent variables have a non-linear relationship (Benoit, 2011). By transforming the distribution, logarithmically transformed variables enhance the fit of the model. Therefore, an improved adjusted R-squared is obtained and Equation (2) is decided as the final model of the regression analysis.

5.6 Discussion

After conducting the multiple regression analysis for the model that was finalized by excluding the outliers, population size and income per capita is found to be statistically significant. The R-squared value indicates how well the model fits the actual data. The R-squared of the final model is 0.6237. However, the R-squared always increases when more variables are included to the model in multiple regression analysis (Wooldridge, 2006). Thus, the preferable measure is adjusted R-squared in this dissertation, to eliminate the variable dependency. The adjusted R-squared value that is obtained by the multiple regression analysis is 0.6192. Therefore, approximately 62% of the variance found in the dependent variable of carbon dioxide emissions can be explained by the independent variables. Several studies that are reviewed in chapter 2 have also found similar R-squared values. To illustrate, Fragkias et al. (2013) estimate R-squared values ranging from 0.67 to 0.68 each ten years by using metropolitan statistical areas, Glaeser et al. (2010) estimate R-squared as 0.41, Gudipudi et al. (2016) find values ranging from 0.6 to 0.71 with different datasets and different threshold distances for the city clustering algorithm, and Oliveira et al. (2014)

obtain an R-squared value of 0.76. Given that similar R-squared values have been obtained in previous studies, the adjusted R-squared of the model used in this dissertation can be considered respectable.

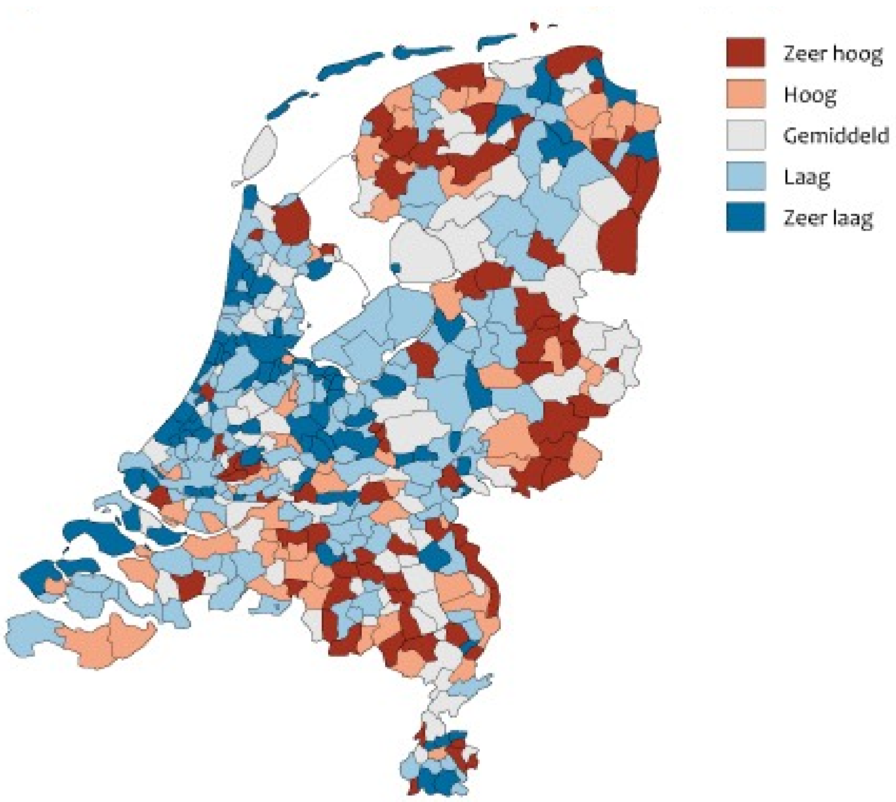
Figure 5.6. log-log Regression of Income per Capita and CO_2 Emissions



A 1% increase in income per capita results a 0.75% decrease in carbon dioxide emissions.

As it is stated in Table 5.3, income per capita has a p-value of 0.02. A p-value is a measure that expresses the probability that observations may have occurred by chance. When the p-value is less than 0.05, it is considered statistically significant. As a consequence, the probability of observations of income per capita happening by chance is 2% which is considered to be a relatively low probability and it is statistically significant. The scaling coefficient of income per capita is -0.75. The scaling coefficient can be described as elasticity (Fragkias, 2013), with a 1% increase in income per capita resulting in a 0.75% decrease in carbon dioxide emissions. Despite the expected outcome based on previous studies, income per capita obtained a negative correlation with carbon dioxide emissions. Büchs et al. (2013) conclude that a 1% increase in equivalised income is associated with a 0.6% increase in total emissions. Similarly, Fragkias et al. (2013) indicates a 1% increase in personal income relates to 0.36% increase in total carbon dioxide emissions in the US. Another study by Hang et al. (2011) confirm that income has a positive effect on carbon dioxide emissions in China. On the contrary, a negative correlation between income and CO_2 emissions also exists in the literature. To clarify, while analyzing relationship between urban form and CO_2 emissions, Makido et al. (2012) obtain for the residential sector, income has negative effects on per capita CO_2 emissions. Further, Gill et al. (2018) identify the scaling coefficient of disposable income as -0.488 with a high significance level in a regression analysis on direct GHG emissions per capita in the UK. Gill et al. (2018) use the concept of suburbanization to explain why there is a negative correlation. Regarding the concept of suburbanization and higher income per capita in the suburbs of larger cities in the Netherlands, the negative correlation in this study is also justifiable.

Figure 5.7. Share of Labour-intensive Industries by Municipalities, 2009

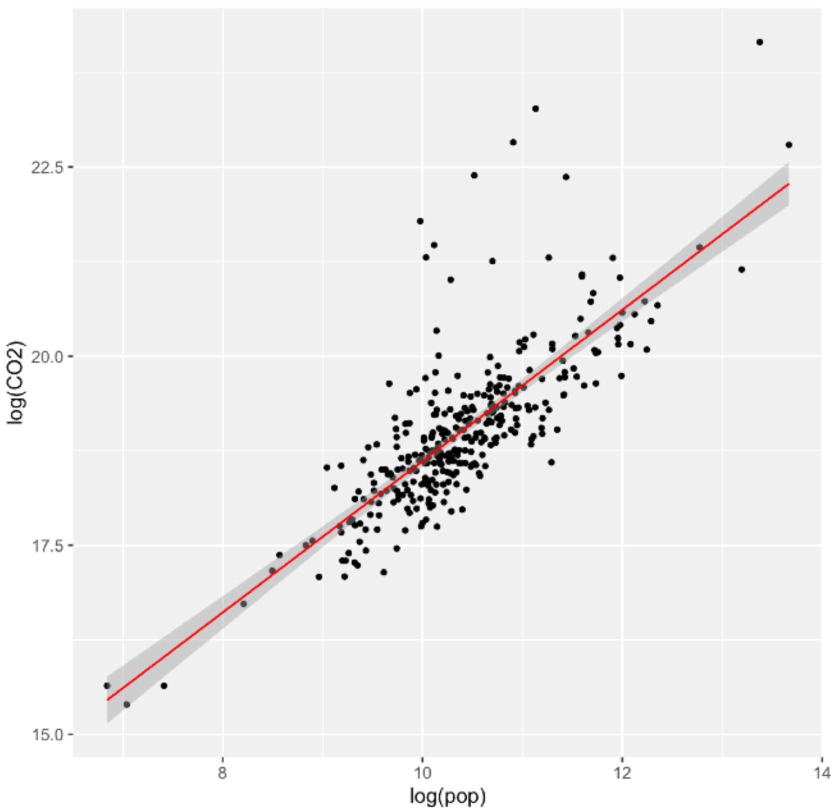


The intensity of labour-intensive industries by municipalities in the Netherlands is shown in the figure. Colors from red to blue represents very high, high, average, low, very low.
Source: *LISA (2009), http://www.lisa.nl/*

Increasing incomes may lead to an increase in consumption in the cities (Gill et al., 2018; Munksgaard et al., 2000). Alternatively, larger incomes earned in cities are not always spent in the city. People may choose to live in smaller municipalities located some distance from the city center if commuting is simple and comfortable. This phenomenon is known as suburbanization (Gill et al., 2018; Siedentop, 2008). Wealthier people may prefer a suburban lifestyle since it allows them to live in single-family dwellings with better opportunities. Although incomes in consumer surveys are assigned to households' locations of residence rather than the place where they are generated, it is expected that higher incomes in wealthy suburbs rather than in the cities themselves under conditions of strong suburbanization (Gill et al., 2018). According to 2018 data of the Netherlands, Wassenaar, Bloemendaal, Blaricum, and Laren have the highest income per capita with 59.2, 56.2, 53 and 52.6 thousand euros respectively. Wassenaar is considered as suburb of The Hague ('s-Gravenhage). Bloemendaal is in the same province as Amsterdam, with a close location. Blaricum and Laren are the suburbs of the Amsterdam metropolitan area. Considering the suburbs of the randstads have the highest income per capita and the randstads -the four largest Dutch cities, which are Amsterdam, Rotterdam, The Hague and Utrecht- have relatively large CO_2 emissions, the case of a negative correlation between income per capita and CO_2 emissions is reasonable.

Further, the share of labour-intensive industries by municipalities in the Netherlands is shown in Figure 5.7 for the year 2009. (Share in knowledge-intensive and capital-intensive industries by municipalities is found in Appendix B) According to the municipalities, their share of the industry sector is 'very high' (labour-intensive, knowledge-intensive, and capital-intensive), their potential economic base is considered industry in this dissertation. The category of very high intensity strongly varied between the minimum and the mean of income per capita. The lowest income per capita belongs to the municipality of Pekela with 24.9 thousand euros and, the mean is approximately 32.4 thousand euros, as is indicated by Table 4.2, Descriptive Statistics. Especially, the nether portion of the poorer municipalities is dominated by labour-intensive industry. In contrast, after the mean threshold, industry as a potential economic base is rarely encountered until the maximum value of income per capita. This situation has strongly prevailed between income per capita of 36 thousand euros and 59.2 thousand euros, which is the municipality of Wassenaar with the highest income per capita of the country. Accordingly, lower income per capita could be associated to industry concentrated municipalities. Dodman indicates that, whether it is primarily industrial or service-oriented, greenhouse gas emissions can be associated with different sectors that reflect the economic base of different cities (2011). Assuming poorer municipalities' potential economic base is industry, the negative correlation between income per capita and CO_2 emissions is reasonable.

Figure 5.8. log-log Regression of Population size and CO_2 Emissions



A 1% increase in population size results a 1.03% increase in carbon dioxide emissions.

The next independent variable that is highly significant is population size. It has a p-value smaller than 2e-16, which is significantly lower than 0.001. Thus, the probability of observations of population size happening by chance is greatly close to zero. Further, the power-law relationship between carbon dioxide emissions and population size represents a positive correlation according to the scaling coefficient. The scaling coefficient of population size is 1.03. This suggests that a 1% increase in population size is associated with a 1.03% increase in CO_2 emissions. The regression results indicate an almost proportional relationship between population size and carbon dioxide emissions. Hence, larger municipalities in terms of population size are insignificantly more emissions efficient than smaller municipalities due to the coefficient of 1.03 is slightly bigger than one (one indicates linearity). In fact, the scaling coefficient is greatly close to one, the scaling behavior can be considered as linear. The change in nonlinear properties of how cities work exhibits either sublinear behavior, meaning that quantities grow more slowly than city size, or superlinear behavior, meaning that quantities grow faster than city size (Bettencourt et al., 2020). Whereas sublinearity indicates the presence of economies of scale, superlinearity indicates the presence of increasing returns to scale. In the case of the Netherlands, with regard to city size and CO_2 emissions, it can be interpreted that there is no considerable amount of economies of scale, likewise, no diseconomies of scale.

As noted in Chapter 2: Literature Review, on the basis of their conclusions and scaling coefficients, numerous studies vary considerably. As a result of adopting differing boundary definitions, Oliveira et al. (2014) discovered two separate findings. While the City Clustering Algorithm demonstrates a superlinear scaling behavior between CO_2 emissions and city population across all US cities with a scaling coefficient of 1.38, the administrative boundaries (MSA) show a sublinear relationship with a scaling coefficient of 0.92. Oliveira et al. (2014) draw the conclusion that larger cities are not more efficient as a result of their study. Alternatively, another study that uses a model to analyze the relationship between CO_2 emissions, economic scale, technology, income, and the population in China by Hang et al. obtains the scaling coefficient of population as 0.9 (2011). While the population has a positive effect on CO_2 emissions, the coefficient indicates a sublinear relationship between the population and CO_2 emissions in China. Admittedly, neither sublinear nor superlinear scaling behaviors, as reported by Oliveira et al. (2014) and Hang et al. (2011), coincide with the population size coefficient obtained in this dissertation, despite the fact that administrative boundaries are adopted in those studies as the boundary unit. Considering countries across the globe have distinct geographical, political, socioeconomic, and sociocultural contexts, relative contrasting results might be reasonable. However, according to the majority of existing literature, including previous studies cited above, the scaling behavior of the population size and CO_2 emissions in the case of the Netherlands meet neither of the both contrasting expected outcomes.

Nonetheless, the population findings of Fragkias et al. (2013) in their study correspond to the findings of this dissertation. Their study is conducted in the United States and 366 metropolitan statistical areas and 576 micropolitan areas are adopted. First, they describe that a 1% increase in population size is related with slightly sublinear increase in CO_2 emissions of 0.93% for the year of 2008. Then, by including a measure of population density and per capita personal income as control variables, the population size coefficient shifts to 1.028, which displays a quite proportional effect for the same year. According to the outcomes of Fragkias et al. (2013), coefficients varied from 1.02–1.03 throughout all the years in their analysis. Thus, it can be seen that the effect of the population size on carbon dioxide emissions in the Netherlands is significantly parallel to the study of Fragkias et al. (2013), with the coefficient of 1.03. CO_2 emissions are determined by the carbon intensity of the energy source as well as demand drivers for fossil fuels, therefore, linear scaling of CO_2 emissions and population size can be justified by several possible explanations (Fragkias et al., 2013). Such as, larger cities might underperform in their capacity to control demand for fossil fuels compared to smaller cities. Or, citizens in larger cities may not be motivated through urban form or energy prices to request lower fossil fuel amounts in their energy supply. Likewise, another possible explanation is that, despite larger cities tend to be more innovative than smaller ones, they may struggle to integrate eco-innovations into local fossil fuel markets. Although the findings in this dissertation are not detailed enough to prove these possible explanations' accuracy, these assumptions seem to be well-grounded and can not be disregarded also for the Netherlands.

Lastly, household natural gas consumption and household electricity consumption have p-values of 0.09 and 0.53 respectively. As it was discussed previously, when the p-value is more than 0.05, the variable is not statistically significant. Both p-values are bigger than the significance level of 0.05. Therefore, these independent variables can not be considered statistically significant. Accordingly, household natural gas consumption and household electricity consumption do not contribute to the variation in CO_2 emissions. In other words, considering these independent variables to explain the relationship with CO_2 emissions is not compatible to the regression analysis.

The findings presented here should be viewed in the context of the limitations. The dissertation has some limitations that could be addressed in future research. The primary limitation is access to other possible independent variables. In order to use the same boundary unit for the municipalities, data is taken from the same source, which is the Netherlands Central Bureau of Statistics (CBS). Although possible related data as independent variables has been used, additional variables could be used to better explain the model and investigate the relationships. As an example, to confirm the possible reasons to explain scaling behavior of population size and CO_2 emissions indicated through the discussion part, fossil fuel consumption and energy prices may be included in the study. Further, the industrial sector as the potential economic base of some municipalities has been considered for the possible reason of the negative correlation between income per capita and CO_2 emissions. Not only to discuss possible reasons behind the negative correlation, but to investigate their empirical relationship and to better explain the association, the level of industry in the municipalities may be included in the study as an independent variable.

CHAPTER 6: CONCLUSION

Cities are responsible for more than 70% of global emissions while occupying only 0.4-0.9 percent of the land surface (Reckien et al., 2007; Ribeiro et al., 2019). CO_2 emissions from urban consumption have dominated global total emissions, and rapidly rising urban CO_2 emissions are one of the primary causes of the exponential rise in global levels (Cai et al., 2013; Dhakal, 2009; IEA, 2009; Satterthwaite, 2008; UN-Habitat, 2011). In light of the undeniable urgency of predictive and quantitative urban organization theory and sustainable development, this dissertation is conducted to primarily identify the power law relationship between CO_2 emissions and the city size in terms of population in the Netherlands.

In order to perform this research, a multiple regression model is conducted. This model is obtained by using population size, income per capita, household natural gas consumption, and household electricity consumption as independent variables to find their relationship with CO_2 emissions. Moreover, before applying the method of OLS to estimate the multiple regression model, linearity, random sampling, conditional mean zero, no perfect collinearity and homoscedasticity assumptions are held true. This yields that the model is applicable to the relevant set of data of the Netherlands.

Regression analysis is conducted both on entire observations and on observations without outliers. Although there were no significant differences, the model that had no outliers is chosen (Model (2)) to create an altered version of regression analysis. Consequently, approximately 62% of the variance found in the dependent variable of carbon dioxide emissions can be explained by the independent variables, whereas the model has produced respectable results.

The results of regression analysis indicated a significant association between population size, income per capita and carbon dioxide emissions in the Netherlands. The city size, in terms of population, and CO_2 emissions are positively correlated. A 1% increase in population size is associated with a 1.03% increase in CO_2 emissions. Despite the expected outcome, the analysis presented almost a linear relationship, indicating that there is neither a considerable amount of economies nor diseconomies of scale. Therefore, in the case of the Netherlands, it is not conceivable to suggest a carbon dioxide efficiency with regard to the city size. Furthermore, it is also found that there is a negative correlation between income per capita and CO_2 emissions. A 1% increase in income per capita resulted in a 0.75% decrease in carbon dioxide emissions. The possible reasons for the negative correlation are specified as the concept of suburbanization and the association between poorer municipalities with industry as their potential economic base. Moreover, household natural gas consumption and electricity consumption are not found to be statistically significant. For this reason, the regression analysis did not allow these independent factors to be used to explain their association with CO_2 emissions.

In conclusion, population size and income per capita are crucial determinants of carbon dioxide emissions in the Netherlands. Despite the fact that the results do not display economies or diseconomies of scale concerning population size and CO_2 emissions, population size still affects the rise of CO_2 emissions. Thus, the decision makers' obligation to develop strategies for low carbon municipalities remains highly critical.

BIBLIOGRAPHY

Arcaute, E., Hatna, E., Ferguson, P., Youn, H., Johansson, A., & Batty, M. (2013). City boundaries and the universality of scaling laws. arXiv:1301.1674.

Arcaute, E., Hatna, E., Ferguson, P., Youn, H., Johansson, A., & Batty, M. (2015). Constructing cities, deconstructing scaling laws. *Journal of The Royal Society Interface*, *12*(102), 20140745. https://doi.org/10.1098/rsif.2014.0745

Batty, M. (2008). The size, scale, and shape of cities. *Science*, *319*(5864), 769–771. https://doi.org/10.1126/science.1151419

Batty, M., & Ferguson, P. (2011). Defining City Size. *Environment and Planning B: Planning and Design*, *38*(5), 753–756. https://doi.org/10.1068/b3805ed

Benoit, K. (2011). *Linear Regression Models with Logarithmic Transformations*. https://kenbenoit.net/assets/courses/ME104/logmodels2.pdf

Bettencourt, L., Lobo, J., Helbing, D., Kühnert, C. & West, G. B. (2007). Growth, innovation, scaling, and the pace of life in cities. Proceedings of the *National Academy of Sciences of the United States of America*, 7301–7306.

Bettencourt, L., & West, G. (2010). A unified theory of urban living. *Nature* 467, 912–913. https://doi.org/10.1038/467912a

Bettencourt, L., Lobo, J., & Youn, H. (2013). The hypothesis of urban scaling: formalization, implications and challenges. *arXiv: Physics and Society*.

Bettencourt, L. (2013). The Origins of Scaling in Cities. *Science, 340*, 1438 - 1441.

Bettencourt, L., & Lobo, J. (2016). Urban scaling in Europe. *Journal of the Royal Society Interface, 13*.

Bettencourt, L., Yang, V., Lobo, J., Kempes, C., Rybski, D., & Hamilton, M. (2020). The interpretation of urban scaling analysis in time. *Journal of the Royal Society Interface, 17*.

Büchs, M., & Schnepf, S. (2013). Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions. *Ecological Economics, 90*, 114-123.

Cai, B., & Zhang, L. (2014). Urban CO2 emissions in China: Spatial boundary and performance comparison. *Energy Policy, 66*, 557-567.

Cottineau, C., Hatna, E., Arcaute, E., & Batty, M. (2017). Diverse cities or the systematic paradox of Urban Scaling Laws. *Computers, Environment and Urban Systems, 63*, 80-94.

Dhakal, S. (2009). Urban energy use and carbon emissions from cities in China and policy implications. *Energy Policy*, 37, 4208-4219. https://doi.org/10.1016/j.enpol.2009.05.020

Dodman, D. (2011). Forces driving urban greenhouse gas emissions. *Current Opinion in Environmental Sustainability, 3*, 121-125.

Fragkias, M., Lobo, J., Strumsky, D., & Seto, K. (2013). Does Size Matter? Scaling of CO2 Emissions and U.S. Urban Areas. *PLoS ONE, 8.*

Frost, J. (2013). *What Are the Effects of Multicollinearity and When Can I Ignore Them?* https://blog.minitab.com/en/adventures-in-statistics-2/what-are-the-effects-of-multicollinearity-and-when-can-i-ignore-them

Gaigné, C., Riou, S., & Thisse, J., (2012). Are compact cities environmentally friendly? *Journal of urban Economics*, 123-136.

Gill, B., & Moeller, S. (2018). Analysis GHG Emissions and the Rural-Urban Divide. A Carbon Footprint Analysis Based on the German Official Income and Expenditure Survey. *Ecological Economics*, *145*, 160-169.

Glaeser, E.L., & Kahn, M.E. (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics*, *67*, 404-418. https://doi.org/10.1016/j.jue.2009.11.006

Gudipudi, R., Fluschnik, T., Ros, A. G. C., Walther, C. & Kropp, J. P. (2016). City density and CO_2 efficiency. *Energy Policy*, *91*, 352–361.

Hang, G., & Yuansheng, J. (2011). The Relationship between CO2 Emissions, Economic Scale, Technology, Income and Population in China. *Procedia environmental sciences, 11*, 1183-1188. https://doi.org/10.1016/j.proenv.2011.12.178

Louf, R., & Barthelemy, M. (2014a). Scaling: Lost in the Smog. *Environment and Planning B: Planning and Design, 41*, 767 - 769.

Louf, R., & Barthelemy, M. (2014b). How congestion shapes cities: from mobility patterns to scaling. *Scientific Reports, 4*.

Makido, Y.K., Dhakal, S., & Yamagata, Y. (2012). Relationship between urban form and CO2 emissions: Evidence from fifty Japanese cities. *urban climate, 2*, 55-67.

Mohajeri, N., Gudmundsson, A. & French, J. R. (2015). CO_2 emissions in relation to street-network configuration and city size. *Transportation Research Part D: Transport and Environment*, *35*, 116–129. https://doi.org/10.1016/j.trd.2014.11.025

Molinero, C., & Thurner, S. (2019). How the geometry of cities explains urban scaling laws and determines their exponents. *arXiv: Physics and Society*.

Montgomery, D.C., & Runger, G.C. (2003). Applied Statistics and Probability for Engineers. John Wiley and Sons.

Munksgaard, J., Pedersen, K.A., & Wien, M., (2000). Impact of household consumption on CO_2 emissions. *Energy Economics*, *22*, 423–440.

Oliveira, E., Andrade, J. & Makse, H. (2014). Large cities are less green. *Scientific Reports*, *4*, 4235. https://doi.org/10.1038/srep04235.

Osbourne, J.W., & Waters, E. (2002). Four Assumptions of Multiple Regression That Researchers Should Always Test. *Practical Assessment, Research and Evaluation, 8*, 2.

Rawlings, J.O., Pantula, S.G. & Dickey, D.A. (1998). Applied Regression Analysis: A Research Tool. 2nd Edition, *Springer.* https://doi.org/10.1007/b98890

Reckien, D., Ewald, M., Edenhofer, O., & Lüdeke, O.M.K. (2007). What parameters influence the spatial variations in CO2 emissions from road traffic in berlin? Implications for urban planning to reduce anthropogenic CO2 emission. *Urban Studies, 44*, 339–355.

Ribeiro, H.V., Rybski, D. & Kropp, J.P. (2019). Effects of changing population or density on urban carbon dioxide emissions. *Nature Communications,* 10, 3204. https://doi.org/10.1038/s41467-019-11184-y

Satterthwaite, D. (2008). Cities' contribution to global warming:notes on the allocation of greenhouse gas emissions. *Environment and Urbanization*, *20*, 539–549.

Siedentop, S. (2008). Die Rückkehr der Städte? Zur Plausibilität der Reurbanisierungshypothese. *Informationen zur Raumentwicklung*, 193–210.

Sykes, A.O. (1993). An Introduction to Regression Analysis. *Coase-Sandor Institute for Law & Economics Working Paper*, *20*.

The Association of Netherlands Municipalities (2020). *Local Government in The Netherlands.*

United Nations, Department of Economic and Social Affairs, Population Division (2019). *World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420)*. New York: United Nations.

UN-Habitat (2011). *Cities and climate change : global report on human settlements, 2011 / United Nations Human Settlements Programme*. Earthscan, London.

Wooldridge, J. M. (2006). *Introductory econometrics: A modern approach*. Mason, OH: Thomson/South-Western.

Appendix A: The Netherlands 2018 dataset

The table displays the dataset used in multiple regression analysis, consists of 343 observations including outliers.

Municipalities	CO_2 emissions	Population size	Income per capita	Natural gas consumption	Electricity consumption
s-Gravenhage	1526100000	537833	33700	1060	2400
s-Hertogenbosch	704170000	154205	34300	1220	2910
Aa en Hunze	238274000	25386	31800	1900	3140
Aalsmeer	139972000	31728	36800	1410	3130
Aalten	106363000	27011	28000	1480	2810
Achtkarspelen	129780000	27852	26200	1630	2660
Alblasserdam	92290700	20069	31600	1260	3110
Albrandswaard	88849600	25271	40100	1200	2530
Alkmaar	1392510000	108558	31900	1350	2770
Almelo	358848000	72849	27300	450	2940
Almere	528369000	207904	32700	1230	2840
Alphen aan den Rijn	328472000	110986	34000	1800	3700
Ameland	18340400	3673	27800	1130	2740
Amersfoort	566647000	156286	36000	1210	2780
Amstelveen	292189000	90838	42008	870	2090
Amsterdam	7934430000	862965	36600	1390	2790
Apeldoorn	862201000	162445	31800	1430	2440
Appingedam	41677600	11721	27400	1110	2440
Arnhem	732554000	159265	30400	1340	2570
Assen	246636000	67963	30100	1600	3550
Asten	214488000	16710	30400	1760	3530
Baarle-Nassau	39761900	6847	29700	1570	2860
Baarn	118288000	24767	38700	1130	3230
Barendrecht	206384000	48673	38000	1540	3180
Barneveld	517700000	57971	31500	1600	3070
Beemster	113963000	9748	36300	1460	3250
Berg en Dal	166597000	34773	30700	1510	2990
Bergeijk	89166100	18491	31800	1710	3630
Bergen (L.)	101419000	13140	28400	1620	3540

Bergen (NH.)	100628000	29974	36800	1680	2890
Bergen op Zoom	645062000	66811	31200	1240	2930
Berkelland	258768000	43904	28600	1610	2910
Bernheze	219641000	30806	31600	1640	3650
Best	162337000	29821	34800	1440	3330
Beuningen	488387000	25882	32700	1430	3120
Beverwijk	162928000	41176	31500	1200	2590
Bladel	110742000	20175	31100	1530	3380
Blaricum	51836000	11202	53000	2090	3900
Bloemendaal	69292000	23410	56200	2080	3520
Bodegraven-Reeuwijk	233962000	34462	35200	1420	3080
Boekel	54075800	10588	29500	1670	3690
Borger-Odoorn	141887000	25372	28800	1880	3150
Borne	89178800	23210	32200	1440	3140
Borsele	1790620000	22800	31000	1390	2760
Boxmeer	239942000	29065	30800	1540	3320
Boxtel	188651000	30747	31500	1400	3060
Breda	845635000	183873	34100	1040	2880
Brielle	108184000	17182	37200	1270	3100
Bronckhorst	247868000	36212	30200	1760	3200
Brummen	312712000	20698	30800	1580	2900
Brunssum	104929000	28103	27600	1350	2850
Bunnik	108414000	15192	39000	1520	3090
Bunschoten	73850500	21576	31600	1450	3470
Buren	115934000	26568	33800	1770	3460
Capelle aan den IJssel	168180000	66818	32500	790	2820
Castricum	112422000	35772	36300	1490	2770
Coevorden	212392000	35483	29000	1720	3100
Cranendonck	131828000	20440	31300	1660	3510
Cuijk	298878000	24931	29600	1420	3070
Culemborg	92128400	28555	33500	1130	2650
Dalfsen	133448000	28499	30800	1690	3180
Dantumadiel	64564800	18923	26300	1650	2560
De Bilt	208145000	42824	41700	1640	3130

De Fryske Marren	320811000	51430	29800	1520	2690
De Ronde Venen	228938000	44059	38500	1500	3250
De Wolden	165029000	24110	30800	1850	3250
Delft	369761000	103163	30100	950	2420
Delfzijl	2106390000	24716	27700	1560	2550
Den Helder	176479000	55604	29000	1270	2400
Deurne	226384000	32362	30100	1590	3450
Deventer	412233000	99957	30500	1200	2680
Diemen	1334150000	29196	33300	970	2660
Dinkelland	134886000	26350	29700	1890	3590
Doesburg	31702000	11148	28700	1260	2710
Doetinchem	245992000	57555	29600	1350	2760
Dongen	187231000	26051	31600	1390	3260
Dordrecht	997980000	118654	31400	1160	2640
Drechterland	77405000	19597	31100	1560	3000
Drimmelen	181563000	27150	32700	1480	3260
Dronten	288673000	40815	30900	1330	2820
Druten	104924000	18797	31300	1460	3120
Duiven	678537000	25332	31500	570	3020
Echt-Susteren	210790000	31638	30800	1620	3250
Edam-Volendam	115019000	36099	34000	1630	3360
Ede	662785000	115710	31700	1370	2890
Eemnes	85029700	9113	35900	1540	3130
Eersel	128333000	19110	34500	1650	3470
Eijsden-Margraten	137633000	25658	33500	1760	3290
Eindhoven	949368000	231642	32600	1210	2610
Elburg	118299000	23086	29200	1510	2980
Emmen	794175000	107113	27100	1570	2930
Enkhuizen	48472900	18507	30000	1250	2690
Enschede	1368580000	158986	26900	1150	2780
Epe	183032000	33145	30700	1710	3130
Ermelo	173557000	26858	32500	1520	2850
Etten-Leur	251026000	43774	32400	1310	3250
Geertruidenberg	2891180000	21515	31900	1220	3070

Geldrop-Mierlo	155699000	39595	32500	1460	3070
Gemert-Bakel	140951000	30447	30100	1570	3490
Gennep	81568800	17071	29800	1540	3300
Gilze en Rijen	130988000	26431	31300	1380	3200
Goeree-Overflakkee	248580000	49611	32800	1400	2990
Goes	174193000	37653	31100	1210	2610
Goirle	66567800	23793	33200	1400	3400
Gooise Meren	327381000	57715	46900	1650	3030
Gorinchem	238180000	36682	32100	1100	2700
Gouda	213450000	73181	32700	1120	2500
Grave	37093200	12483	31200	1490	3150
Groningen	1001890000	203819	28700	1200	2210
Gulpen-Wittem	59192800	14246	30500	1640	3090
Haaksbergen	94388200	24277	29500	1580	3260
Haaren	69436800	14195	34400	1680	3580
Haarlem	374011000	161265	36300	1230	2420
Haarlemmermeer	1777040000	148068	36400	1270	3030
Halderberge	138680000	30194	31400	1530	3210
Hardenberg	320751000	60574	28100	1600	3240
Harderwijk	218619000	47581	31200	1260	2720
Hardinxveld-Giessendam	109543000	18051	31200	1280	2970
Harlingen	337363000	15758	27400	1340	2220
Hattem	122793000	12173	33000	1570	2800
Heemskerk	99690500	39164	32400	1230	2660
Heemstede	70520100	27286	49000	1640	3000
Heerde	198020000	18546	30700	1670	3030
Heerenveen	263276000	50257	30200	1440	2540
Heerhugowaard	194613000	56742	31500	1090	2760
Heerlen	361901000	86832	27400	1250	2670
Heeze-Leende	102997000	15964	35700	1750	3470
Heiloo	72790400	23464	37000	1530	2840
Hellendoorn	136911000	35808	29400	1610	3180
Hellevoetsluis	131704000	40049	34700	1170	3070
Helmond	367604000	91524	30200	1090	3040

Hendrik-Ido-Ambacht	89203800	30966	35700	1180	3030
Hengelo (O.)	571093000	80683	29700	1350	2830
Heumen	84740300	16486	35400	1570	3090
Heusden	244645000	44135	32200	1490	3370
Hillegom	53293100	21966	33300	1240	2870
Hilvarenbeek	81705300	15334	33000	1660	3490
Hilversum	289186000	90238	37700	1450	2640
Hof van Twente	197652000	34940	30200	1680	3260
Hollands Kroon	366156000	47815	29800	1520	3000
Hoogeveen	306042000	55662	27400	1470	2780
Hoorn	173995000	73004	31100	1200	2700
Horst aan de Maas	391010000	42291	29800	1640	3520
Houten	170255000	49911	38800	950	3090
Huizen	113389000	41273	35800	1390	2850
Hulst	180833000	27524	31900	1460	2720
IJsselstein	83002200	34160	35200	1150	3030
Kaag en Braassem	181239000	26866	34300	1400	3110
Kampen	254190000	53779	28600	1370	2760
Kapelle	145271000	12785	32000	1350	2770
Katwijk	150908000	65302	31700	1190	2860
Kerkrade	154073000	45642	26700	1390	2750
Koggenland	142496000	22738	31200	1480	3060
Krimpen aan den IJssel	62280200	29376	32800	1290	2830
Krimpenerwaard	212245000	56048	33000	1400	2970
Laarbeek	165042000	22333	31100	1580	3440
Landerd	101729000	15529	30600	1690	3700
Landgraaf	114878000	37591	28900	1430	2900
Landsmeer	30508500	11488	38300	1500	3160
Langedijk	80251600	27992	32300	1270	2900
Lansingerland	605716000	61601	39800	1200	3300
Laren (NH.)	73404100	11195	52600	2240	3690
Leeuwarden	525665000	123107	28300	1260	2230
Leiden	506158000	124899	33300	930	2350
Leiderdorp	88937300	27109	36500	1140	2820

Leidschendam-Voorburg	262152000	75425	38500	1250	2550
Lelystad	1783150000	77893	30100	1070	2880
Leudal	284475000	35681	30700	1660	3460
Leusden	121656000	30030	36800	1380	3060
Lingewaard	302431000	46475	32000	1460	3040
Lisse	55853000	22800	33200	1220	2780
Lochem	244760000	33590	33300	1790	3050
Loon op Zand	87353000	23327	31200	1480	3320
Lopik	78392900	14473	32200	1530	3420
Loppersum	51300900	9614	29300	1790	2630
Losser	96925100	22622	28700	1660	3290
Maasdriel	223713000	24693	32200	1730	3340
Maasgouw	137752000	23716	31600	1700	3300
Maassluis	63806300	32768	31400	1120	2670
Maastricht	1116630000	121565	29300	1210	2570
Medemblik	250645000	44809	30400	1490	2960
Meerssen	82457500	18923	33900	1710	3300
Meierijstad	533971000	80815	31400	1510	3400
Meppel	164648000	33564	30900	1350	2670
Middelburg (Z.)	206303000	48544	30900	1190	2390
Midden-Delfland	298334000	19391	36700	1230	3070
Midden-Drenthe	289014000	33178	29800	1720	3050
Midden-Groningen	548936000	60899	28100	1610	2790
Mill en Sint Hubert	55926100	10891	29300	1710	3670
Moerdijk	5293910000	36961	32600	1430	3230
Montferland	157095000	36026	28600	1550	3070
Montfoort	48994600	13996	34400	1420	3270
Mook en Middelaar	26237100	7806	35900	1730	3380
Neder-Betuwe	261467000	24034	29700	1630	3280
Nederweert	166380000	17001	30100	1650	3620
Nieuwegein	251873000	63036	32200	570	2900
Nieuwkoop	120718000	28628	34000	1460	3120
Nijkerk	205180000	42943	32600	1430	3030
Nijmegen	568160000	176756	29800	1150	2390

Nissewaard	183730000	84797	32700	1100	3000
Noord-Beveland	42252500	7308	29900	1310	2470
Noordenveld	131513000	31290	31000	1710	2850
Noordoostpolder	426576000	46862	29000	1420	2840
Noordwijk	137121000	26174	35500	1370	2870
Nuenen, Gerwen en Nederwetten	93661900	23186	37200	1660	3320
Nunspeet	160942000	27481	30600	1590	3090
Oegstgeest	67421100	24426	47200	1280	2960
Oirschot	175990000	18623	33200	1650	3670
Oisterwijk	124892000	26140	35800	1570	3410
Oldambt	294991000	38129	26700	1700	2780
Oldebroek	136734000	23598	28900	1590	3050
Oldenzaal	117452000	31840	30100	1460	2960
Olst-Wijhe	77537500	18071	30400	1570	3080
Ommen	125757000	17813	29800	1680	3160
Oost Gelre	164322000	29704	30000	1530	2970
Oosterhout	297905000	55616	32100	1250	3060
Ooststellingwerf	130082000	25497	27800	1700	2630
Oostzaan	47235100	9757	35000	1410	3080
Opmeer	52943400	11779	30000	1480	2900
Opsterland	163489000	29723	29400	1640	2720
Oss	392546000	91451	30900	1450	3220
Oude IJsselstreek	176512000	39473	27800	1540	2970
Ouder-Amstel	150758000	13916	42300	1360	2920
Oudewater	32494600	10201	34500	1440	3150
Overbetuwe	329931000	47543	33100	1490	3110
Papendrecht	118093000	32290	33100	1060	2870
Peel en Maas	478525000	43311	29500	1620	3490
Pekela	73053400	12214	24900	1760	2920
Pijnacker-Nootdorp	276697000	54331	38600	1040	3160
Purmerend	119253000	80117	31100	370	2850
Putten	169770000	24198	31400	1590	3240
Raalte	165807000	37511	29700	1550	3050
Reimerswaal	362677000	22678	29100	1350	2800

Renkum	374418000	31302	36400	1640	2750
Renswoude	34989200	5259	33700	1560	3420
Reusel-De Mierden	59625400	13060	31600	1640	3720
Rheden	149742000	43640	31300	1510	2660
Rhenen	71630400	20004	32600	1520	3190
Ridderkerk	246084000	46241	31100	1140	2860
Rijssen-Holten	207043000	38300	29300	1630	3130
Rijswijk (ZH.)	183718000	53467	35000	1200	2480
Roerdalen	106385000	20615	30300	1660	3270
Roermond	583095000	58209	30100	1330	2840
Roosendaal	726424000	77032	30700	1370	2950
Rotterdam	30867700000	644618	30500	850	2350
Rozendaal	6210590	1654	52000	2390	3890
Rucphen	117392000	22572	29300	1750	3700
Schagen	213772000	46553	30900	1440	2870
Scherpenzeel	32512100	9873	31200	1520	3090
Schiedam	238377000	77999	30100	1060	2460
Schiermonnikoog	6211570	936	30700	1680	2590
Schouwen-Duiveland	206630000	33779	31100	1450	2830
Simpelveld	35856300	10516	29800	1580	2920
Sint Anthonis	80909500	11606	30900	1720	3640
Sint-Michielsgestel	103315000	28991	35100	1690	3530
Sittard-Geleen	5174450000	92661	30500	1360	2930
Sliedrecht	103970000	25026	30600	1170	2620
Sluis	126933000	23386	29700	1390	2460
Smallingerland	243727000	55938	28300	1440	2480
Soest	165007000	46194	36300	1530	3120
Someren	200029000	19322	29800	1620	3520
Son en Breugel	185157000	16904	37600	1720	3480
Stadskanaal	118394000	31789	25600	1650	2850
Staphorst	146364000	17003	28500	1830	3480
Stede Broec	51092000	21706	29300	1390	2830
Steenbergen	391441000	25054	30600	1470	3240
Steenwijkerland	202549000	43940	28700	1570	2870

Stein (L.)	80010400	24961	30600	1510	3150
Stichtse Vecht	402816000	64336	38200	1410	3100
Súdwest-Fryslân	456423000	89710	28900	1450	2480
Terneuzen	8195310000	54589	31100	1340	2620
Terschelling	28435700	4890	30000	1700	2750
Texel	81860500	13547	28500	1520	2720
Teylingen	117378000	37061	37900	1300	2980
Tholen	152629000	25780	29400	1330	2880
Tiel	227865000	41978	30200	1330	2880
Tilburg	770795000	217259	29300	870	2790
Tubbergen	121663000	21276	29500	1900	3770
Twenterand	118093000	33792	27700	1600	3270
Tynaarlo	139242000	33698	35400	1840	3030
Tytsjerksteradiel	181935000	31780	28900	1590	2600
Uden	198904000	41782	30900	1410	3250
Uitgeest	90790300	13528	35100	1330	2860
Uithoorn	128247000	29424	35100	1280	2850
Urk	64625600	20763	29300	1500	3350
Utrecht	2045170000	352866	35400	790	2400
Utrechtse Heuvelrug	296347000	49515	38800	1670	3170
Vaals	26339200	10092	28700	1450	2690
Valkenburg aan de Geul	70329500	16470	31300	1580	2910
Valkenswaard	104460000	30910	31500	1440	3130
Veendam	226734000	27491	27400	1690	2730
Veenendaal	161829000	65589	30800	1200	2910
Veere	88969500	21835	31500	1450	2670
Veldhoven	162334000	45337	35400	1420	3190
Velsen	1,28E+10	68348	32900	1270	2660
Venlo	633730000	101603	28500	1390	2940
Venray	333579000	43326	29800	1520	3280
Vlaardingen	187883000	72404	30800	1090	2510
Vlieland	4850310	1138	30900	1440	2720
Vlissingen	1704350000	44371	29100	1110	2290
Voerendaal	49016300	12452	33400	1680	3160

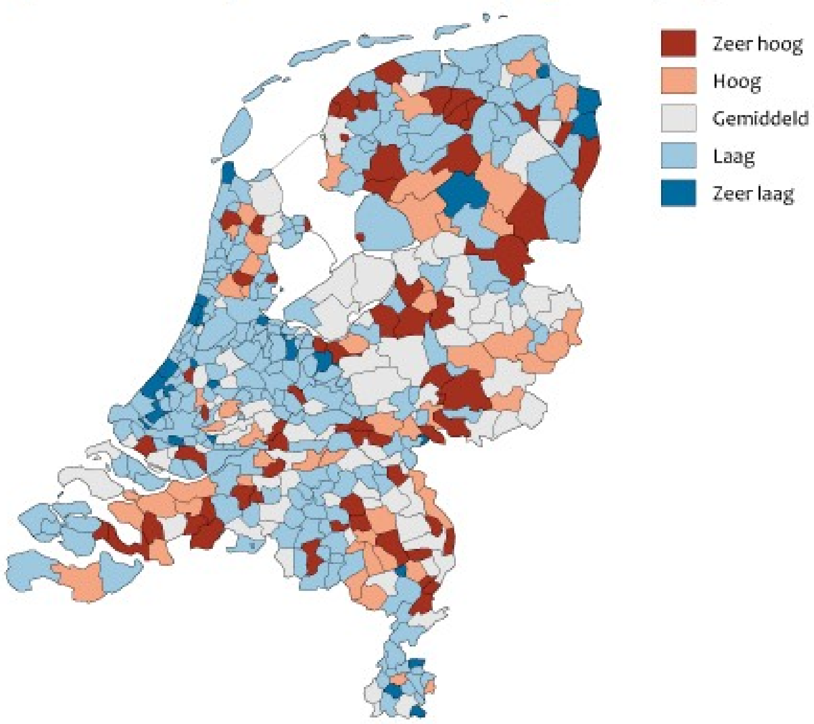
Voorschoten	50886600	25479	40800	1340	2860
Voorst	176926000	24417	31900	1660	3170
Vught	117694000	26396	39500	1540	3140
Waadhoeke	320109000	46039	27800	1520	2550
Waalre	72870000	17247	40700	1750	3270
Waalwijk	220489000	48240	30600	1360	3050
Waddinxveen	175853000	28316	32500	1210	2980
Wageningen	103135000	38774	29700	1160	2400
Wassenaar	117624000	26211	59200	1960	3370
Waterland	77092300	17315	37000	1530	2970
Weert	363827000	49842	30600	1460	3040
Weesp	61093500	19334	36000	1160	2510
West Maas en Waal	120471000	19076	31400	1680	3160
Westerveld	106655000	19348	30700	1840	3130
Westervoort	27809700	14944	29700	810	2850
Westerwolde	225020000	25199	26900	1880	3080
Westland	1429140000	108603	32300	1250	3090
Weststellingwerf	131338000	25840	27700	1630	2740
Westvoorne	108234000	14626	40300	1620	3400
Wierden	139074000	24351	31000	1670	3410
Wijchen	164633000	40951	32000	1360	3050
Wijdemeren	82290400	24013	38200	1680	3210
Wijk bij Duurstede	65646800	23762	34500	1370	3190
Winterswijk	133951000	28903	28400	1510	2860
Woensdrecht	130729000	21866	31800	1520	3330
Woerden	360423000	52197	36300	1300	2950
Wormerland	97607500	16329	33000	1340	2840
Woudenberg	70660800	13166	33200	1490	3160
Zaanstad	615988000	155885	31000	1220	2570
Zaltbommel	306949000	28451	32400	1520	3100
Zandvoort	38170700	17011	34100	1350	2780
Zeewolde	158814000	22309	33500	1050	2980
Zeist	238051000	63934	39900	1470	2930
Zevenaar	281384000	43488	29300	1360	2970

Zoetermeer	338236000	124944	33600	1000	2880
Zoeterwoude	111291000	8450	34800	1310	2930
Zuidplas	312508000	42762	35300	1290	3160
Zundert	121819000	21612	30500	1710	3530
Zutphen	194744000	47609	29600	1280	2490
Zwartewaterland	91875900	22503	29700	1500	3050
Zwijndrecht	232248000	44639	31500	1200	2760
Zwolle	511494000	127497	31900	1170	2580

Appendix B: Types of industries by municipalities

The intensity of capital-intensive and knowledge-intensive industries by municipalities in the Netherlands is shown in the figures. Colors from red to blue represents very high, high, average, low, very low.

Share of Capital-intensive Industries by Municipalities, 2009



Share of Knowledge-intensive Industries by Municipalities, 2009