Prague University of Economics and Business

Faculty of Informatics and Statistics

Wasteful

An Outlook on Municipal and Packaging Waste with Income and International Trade

Master Thesis / Diploma Thesis II

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Abstract
The overall theme for this thesis is waste in Europe, and the theme of waste is explored through municipal waste, packaging waste, and the trade of paper and cardboard waste. In the first two chapters, the aim is to examine the relationship between waste indicators with income using the Environmental Kuznets Curve hypothesis. There was only one instance in the first chapter that the EKC hypothesis is proven. The second chapter did not find any relation that proves the Environmental Kuznets Curve hypothesis. In the third chapter, emphasis is placed on a basic exploration on the structure of waste paper and cardboard trade. All data used in this thesis are sourced from Eurostat. The first two chapters examined the EKC hypothesis using panel regression and the last chapter used network analysis to investigate the structure of the paper and cardboard trade network.

Keywords
Environmental Kuznets Curve, Municipal Waste, Packaging Waste, Network Analysis, Trade of Waste

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Preface

Microplastics and nanoplastics have penetrated all corners of our planet. Both are present in our sewage system (Mahon, et al., 2017), in the food we eat (Barboza, et al., 2018), on the ocean floor (Jamieson, et al., 2019), and even affect the birds roaming in the skies (Carlin, et al., 2020). Microplastics and nanoplastics are everywhere we see (Parker, 2020). Although its effects on humans are relatively unknown, studies have shown that both forms of plastic can induce a change in behavior as well as development in neuronal disorders (Prüst, et al., 2020). It has also been shown that both plastics can possibly cause cellular damage as well as DNA damage in humans (Vethaak & Legler, 2021).

Microplastics are plastic particles that are smaller than 5 millimeters. Nanoplastics are plastic particles that are smaller than 1 micrometer. Microplastics and nanoplastics come from a variety of sources, such as clothing, packaging, cosmetic products, paint, etc. (European Parliament, 2018). As plastic products breakdown, they may fragment into smaller pieces, and thus resulting in micro- and nanoplastics. Microplastics and nanoplastics can take on several forms for example, foam, fibers, or fragments.

A recent study has shown that wastewater treatment plants are ineffective in filtering out microplastic (Kay, et al., 2018). Sources of microplastic and nanoplastic contamination can come from waste, where the run-offs from contaminated land (such as unsanitary landfill of waste) carry these plastic particles to various places (UN Environment Programme, 2020). In order to further curb these contaminations, a better understanding of waste and waste management is needed.

Currently, the waste strategies in EU countries are adopted from the Waste Framework Directive set out by the European Commissions in 2008 (European Parliament and Council, 2018). The directive has outlined a need for prevention of waste and has established a top-down hierarchy in dealing with the management of waste, with waste prevention as the first line of option, followed by re-use, recycling, recover, and disposal (European Commission, 2015). The Commission recommends prevention and re-use as the more preferable strategies for waste management, whereas disposal methods like landfill are the last recourse.

In 2018, construction and mining represent over 60% of total waste generation in the EU (Eurostat, 2020). Finland leads with the highest amount of waste generated (23253 kilograms per capita) and Latvia generated the least amount of waste (920 kilograms per capita) in 2018. On average, the EU27 countries generated 5190 kilograms per capita of waste in 2018. 45.8% of the waste generated in 2018 were simply disposed, which included waste management methods such as incineration without recovery or landfill. Countries such as Greece, Finland, and Sweden prefer simple waste disposal methods. On the other hand, 54.2% of waste generated in 2018 were recovered through methods such as backfilling[1], recycling and energy recovery. Countries such as Slovenia and Denmark have the highest percentage of waste recovery in Europe.

Aim of this Thesis

This paper aims to look at the different facets of municipal and packaging waste. The first chapter deals with municipal waste through various waste operations and its relation to income,

[1] Backfilling is newly introduced waste operation where waste has been repurposed as a substitute for something else (Department for Environment, Food and Rural Affairs , 2012) (Eurostat, 2018). For example, the re-use of bricks from a demolished building. This waste operation is commonly associated with the construction and demolition sector (NWE Secretariat, 2018).

using the Environmental Kuznets Curve (EKC) hypothesis. The second chapter deals with packaging waste and its relation to income using the EKC hypothesis. The third chapter looks at the trade of recyclable paper waste in European countries. Each chapter are outlined with subsections of background information and literature review, data sources and methods, a presentation of results and a small discussion. Finally, this paper ends with a general conclusion on the different points discussed throughout this paper.

Chapter 1: Municipal Waste in Europe

1.1 Introduction

According to the special report by the Intergovernmental Panel on Climate Change, there is a high chance that global warming will increase by 1.5 degree Celsius between 2030 and 2052, if the world continues with the same activities (Intergovernmental Panel on Climate Change, 2018). The report has also projected other risks associated with climate change, such as an increase in average temperature, an increase in sea-level, and an increasing range of extreme weather events. The report has also highlighted that the risks are not only a threat to nature, but also to humanity itself. The report has stated that with the increasing volatility in our climate, humans will face more challenges in terms of health, economic growth, and declining natural resources. With this in mind, there should be a change in how human interacts with the environment, thus call for a new era of sustainable development.

The Brundtland definition of sustainable development is defined as, "development that meets the needs of the present without compromising the ability of future generations to meet their own needs." (World Commission on Environment and Development, 1987). This definition is made famous by the former Norwegian Prime Minister Gro Harlem Brundtland in 1987 in his report called *Our Common Future*. The definition entails that there should be some sort of intergenerational equity and equality. This definition of sustainable development is pillared on three intersections, namely: environment, society, and economy. These three pillars play an integral part in how our actions today can affect the future.

One of the economic theories with regards to sustainable development is the Environmental Kuznets Curve (EKC, hereafter). The EKC hypothesizes that as society evolves, environmental degradation increases up to a certain point and after that point, environmental degradation decreases (Tietenberg & Lewis, 2018). This theory was based on the Kuznets curve, where it was postulated that there is an inverted U-shape relationship between income inequality and income (Tietenberg & Lewis, 2018). The EKC assumes that as society progresses, the understanding and care for the environment increases in demand, and thus after reaching a certain point of societal advancement, environmental degradation will decrease. As Dinda has pointed out (Dinda, 2004), the hypothesis of the EKC is particularly appealing. This is due to the assumption that society and the environment will be better off in the long run. This also meant another underlying assumption that the only way to better the environment is to become richer, and this is in line with the neoclassical schools of economic development.

1.2 Aim of the Chapter

The aim for this chapter is to analyze existing data on municipal waste and income from Eurostat and determine if there are any relationship between the two variables and to test the hypothesis of the Environmental Kuznets Curve. This chapter hypothesizes that there is some sort of relationship between the two variables, but whether the EKC holds true remains a question.

1.3 Background

According to the special report from the World Bank, "global waste is expected to grow to 3.40 billion tons by 2050, more than double population growth over the same period. Overall, there is a positive correlation between waste generation and income level." (Kaza, et al., 2018). The report has highlighted that the daily rate of waste generation for high income countries will set to increase by 19 percent in 2050. The main source of waste in high income countries are recyclable waste such as metal, glass, paper, plastic or cardboard and it accounts for 51% of the total waste produced (Kaza, et al., 2018).

Waste generation and income has always been the focus for several countries. The Norwegian Environment Agency found a direct relationship between waste and GDP (2017). Between the years of 1995 to 2017, the relationship between waste generation and economic growth has always been positive, and the rate of growth for waste has been higher than the rate of economic growth since 2012 in Norway. The agency has commented it is unlikely that the rate of the growth for waste will be lower than the rate of growth of income in the future (Norwegian Environment Agency, 2017). However, the agency believes that with the increasing number of policies targeting waste, the rate of growth in waste generation could be suppressed. This is particularly evident with recycling rates.

A study from Sweden has projected that waste generation will continue to increase without absolute decoupling from income (Sjöström & Östblom, 2010). Sjöström and Östblom has projected the future waste generation using the baseline scenario. The authors have suggested that for an absolute decoupling between waste and income, firms and households need to decrease their waste production. All households should reduce waste by 3.36% per year in order to reach absolute decoupling. A report from the European Commission on this study has suggested a strong policy intervention such as high tax on virgin materials or different tax rates for goods and services depending on the waste generated (European Commission DG ENV, 2010).

Mazzanti et al. have studied the links between income levels and municipal waste generation between Italian provinces (Mazzanti, et al., 2008). The authors have found that there is a turning point at which municipal waste generation decreases. These turning points exists for the wealthier Italian provinces. Upon further analysis, the authors have noted that environmental policies and regulations in waste management are the strong drivers for the decrease in municipal waste generation.

In general, these studies have shown that there is some sort of relationship between income and waste generation in European countries. In Norway and Sweden, the macro trend for waste and income is positive and linear. In Italy, the micro trend for waste and income shows an inverse U relationship, but only with strong policy intervention.

In another study, Mazzanti and Zoboli analyzed the relationship between income and municipal waste generated, landfilled, and incinerated between selected EU countries during the years of 1995 to 2005 (Mazzanti & Zoboli, 2009). The authors used final consumption expenditure of households as the income indicator and municipal solid waste as the waste indicator. Mazzanti and Zoboli found that the relationship between waste generated and income is not an inverse-U trend. However, when examining the relationship between waste incinerated and waste landfilled against income, the authors have found an inverse-U trend. The inverse-U trend is strongly influenced by the adoption of EU directives on waste.

1.4 Data and Methods

This chapter will be lightly based on the previous work of Mazzanti and Zoboli (Mazzanti & Zoboli, 2009) with specific recommendations from Van Alstine and Neumayer (2010). The dependent variable is income. The income variable is expressed as final consumption expenditure of households at current prices in PPS per capita[2]. The independent variable is the municipal waste in kilograms per capita. In this study, we will be looking at total municipal waste

[2] This is coded as P31_S14 on the Eurostat website, under the nama_10_PC data table. Final Consumption Expenditure by Household was chosen because municipal waste mainly accounts for household waste, and such that expenditure of households is a great indicator and corresponds to in terms of income. Final Consumption Expenditure of Households was also used in the Mazzanti and Zoboli paper.

generated[3], landfilled municipal waste[4], and recycled municipal waste of materials[5]. All variables will be natural logged if possible. This is to ensure a smoother interpretation where the model could be interpreted in terms of elasticity and the random errors will be smoothed out.

If the data allows, the main model we will be testing in this chapter is:

$$C = a + b \cdot Y + c \cdot Y^2 + \ d \cdot Y^3 + G(t) + \varepsilon \qquad [1]$$

Where C is the waste produced or repurposed, Y is the Final Consumption Expenditure of Households per capita adjusted by PPS. G(t) is some function of time, ε is the error term, and a is some constant. All variables are expressed in natural logarithms. The points below discuss each scenario of the main model:

- If b = c = d = 0, then there is no relationship between waste generated and household expenditure per capita
- If b > 0 and c = d = 0, then there is a positive linear relationship between waste generated and household expenditure per capita
- If b < 0 and c = d = 0, then there is a negative linear relationship between waste generated and household expenditure per capita
- If b is a natural number, c < 0 and d = 0, then there is a negative parabolic relationship between waste generated and household expenditure per capita (inverted U-shape)
- If b is a natural number, c > 0 and d = 0, then there is a positive parabolic relationship between waste generated and household expenditure per capita (U-shape)
- If b and c are natural numbers, and d > 0, then there is a positive cubic relationship between waste generated and household expenditure per capita (N-shape)
- If b and c are natural numbers, and d < 0, then there is a negative cubic relationship between waste generated and household expenditure per capita (mirrored N-shape)

There are other studies who fit higher degrees of polynomials, but all other even degree polynomials above 2 are all rather similar in shape in comparison to the quadratic model and could lead to overfitting. Similarly, polynomials in odd degrees above 3, are all rather similar in shape in comparison to the cubic model. In this chapter, we will be running panel regression models, and we will be fitting in both fixed effects, random effects, and time effects.

1.5 Comparing Neighboring Countries

In this section, we will be comparing different municipal waste indicators across countries through time. The countries selected for this section are Czechia (Czech Republic), Slovakia (Slovak Republic), Germany, Austria, and Poland, with the EU28 average as a benchmark.

[3] This is coded as GEN on the Eurostat website, under the env_wasmun table.
[4] This is coded as DSP_L_OTH on the Eurostat website, under the env_wasmun table.
[5] This is coded as RCY_M on the Eurostat website, under the env_wasmun table.

1.5.1 Total Municipal Waste

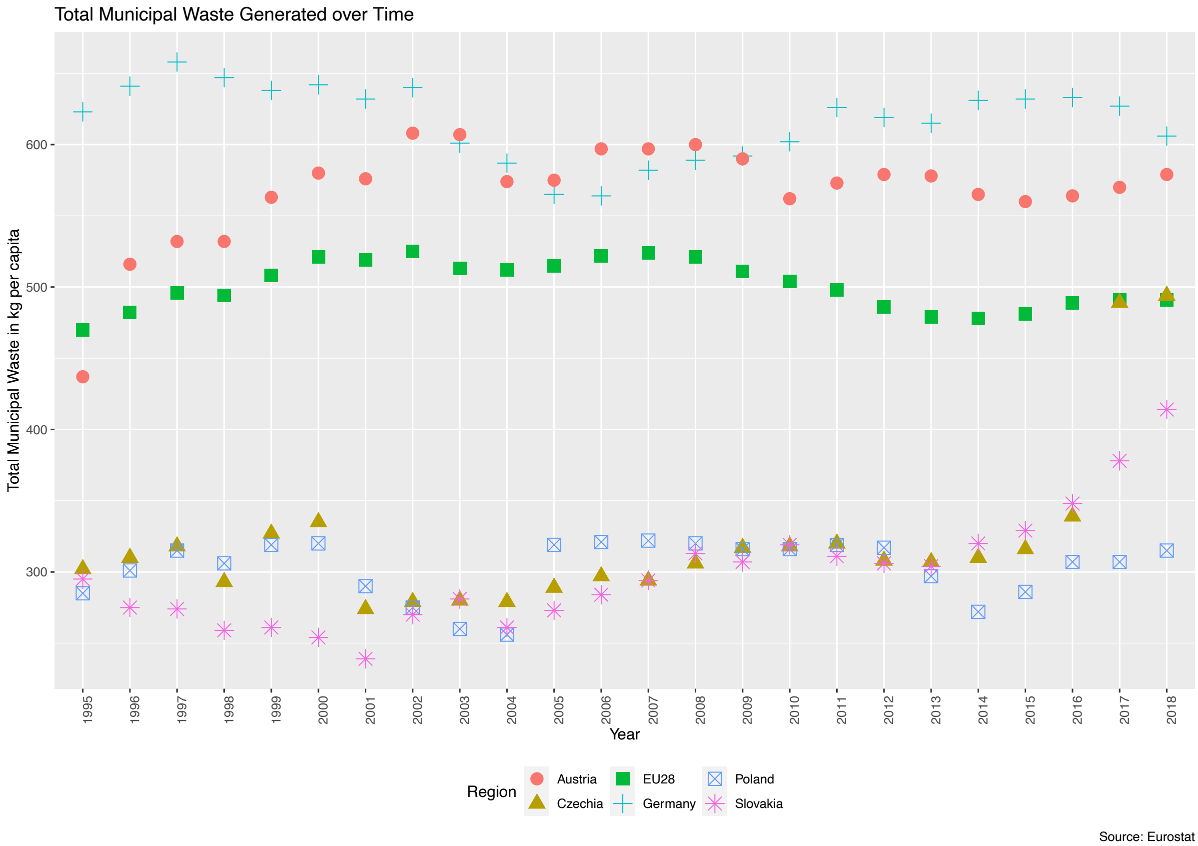


Figure 1: Scatterplot of Total Municipal Waste over Time for Selected countries (1995 - 2018)

Figure 1 shows the total municipal waste over time for neighboring countries of Czech Republic. In 2018, Germany produced the most municipal waste and Poland produced the least municipal waste. Germany and Austria generally produced more municipal waste than the EU28 average across all years examined. On the other hand, Poland, Czech Republic, and Slovakia generally produced less municipal waste than the EU28 average.

It is interesting to note the dramatic increase in the generation of municipal waste for Czech Republic from 2016 to 2017. Starting in 2001, Slovakia has been steadily increasing in the generation of municipal waste. The generation of municipal waste fluctuates around 300 kilograms per capita for Poland and the generation of municipal waste fluctuates around 600 kilograms per capita for Germany.

1.5.2 Landfilled Municipal Waste

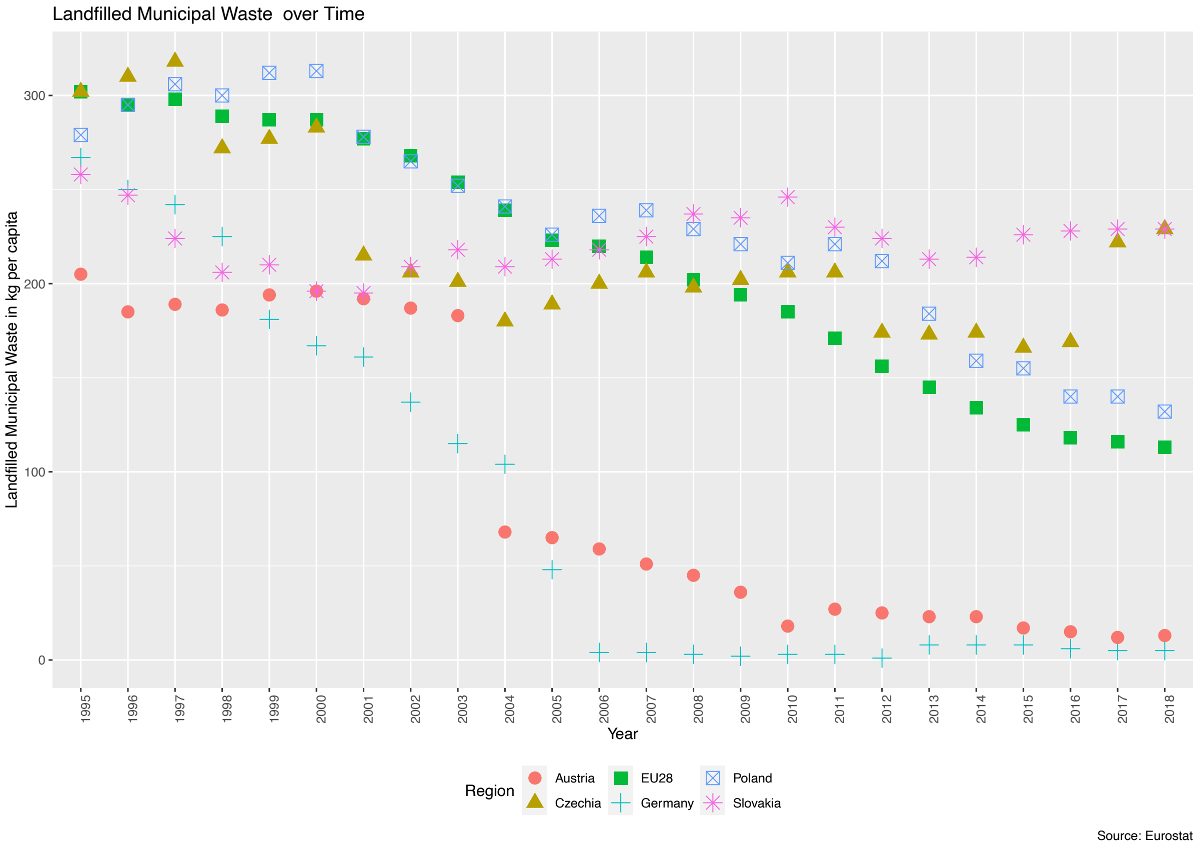


Figure 2: Scatterplot of Landfilled Municipal Waste over Time for Selected countries (1995 - 2018)

Figure 2 shows the scatterplot of landfilled municipal waste over time, dating from 1995 to 2018. Across all countries, the landfilling of municipal waste has been steadily decreasing for all countries besides Slovakia and Czech Republic. Germany and Austria are well below the EU28 average of landfilled municipal waste. Poland, Czech Republic, and Slovakia are above the EU28 average for landfilled municipal waste.

Between 2003 and 2004, Austria has a remarkable decrease in the landfill of municipal waste. Czech Republic has an increase in the landfill of municipal waste between 2016 and 2017. It is important to note that starting from 2006, landfilled municipal waste for Germany is infinitesimal, nearing zero.

1.5.3 Incinerated Municipal Waste for Disposal

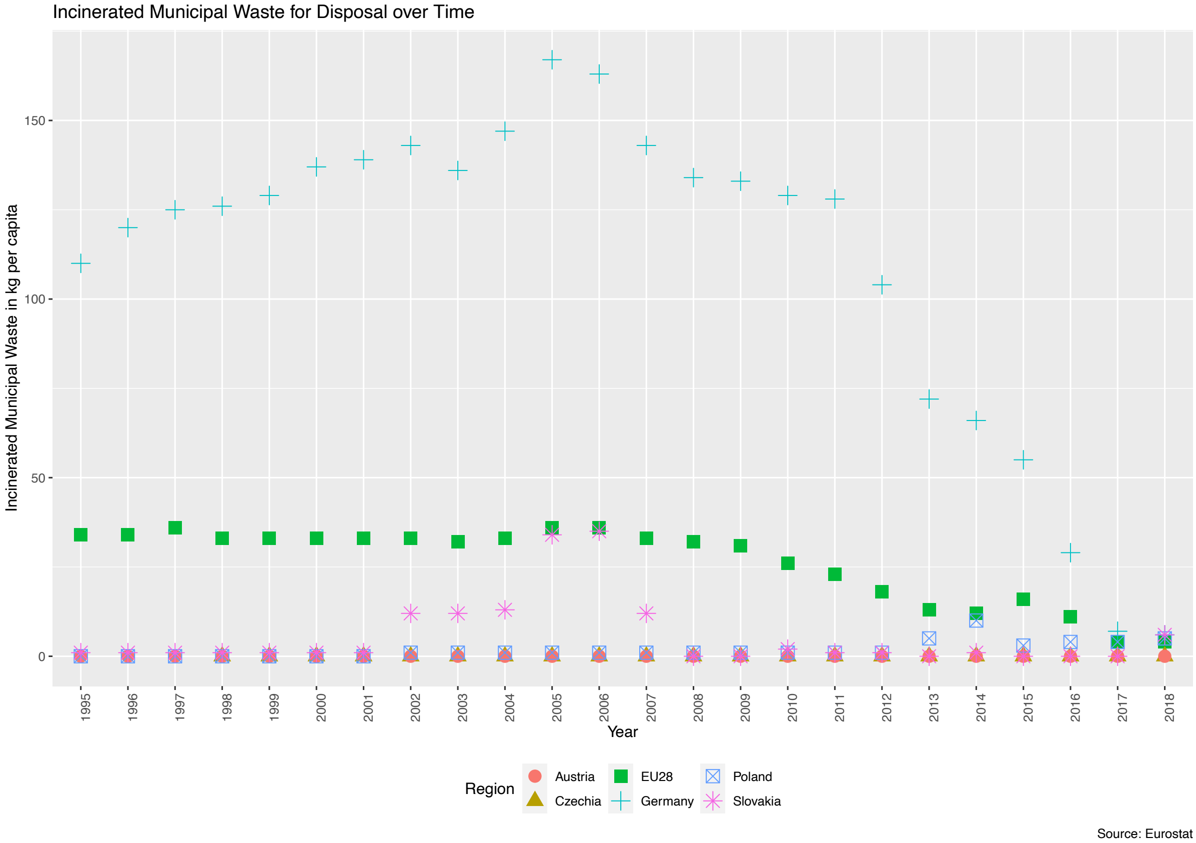


Figure 3: Scatterplot of Incinerated Municipal Waste for Disposal over Time for Selected countries (1995 - 2018)

Figure 3 shows the disposal of municipal waste by incineration in kilograms per capita from 1995 to 2018. It is important to note that for Austria and Czech Republic, the disposal of municipal waste by incineration is zero. This means that both countries do not dispose municipal by means of incineration.

The incineration of waste in Germany increased from 1995 to 2005, and decreased from 2005 to 2018. Although hard to see, Poland increased the incineration of municipal from 2013 onwards. Slovakia temporarily increased the use of incineration between 2002 and 2007.

1.5.4 Recovered Municipal Waste for Energy[6]

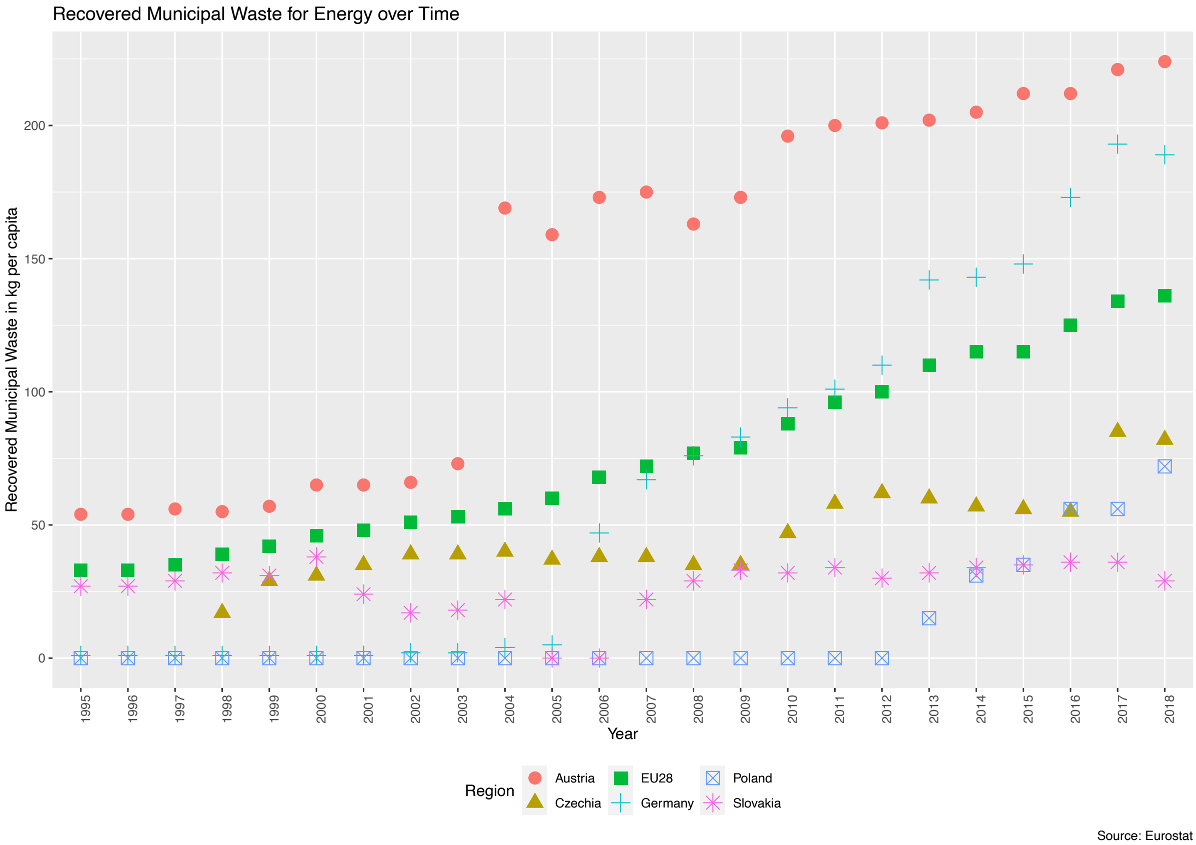


Figure 4: Scatterplot of Recovered Municipal Waste for Energy over Time for Selected countries (1995 - 2018)

Figure 4 shows the use of municipal waste by energy recovery. In almost all countries, energy recovery through municipal waste increased throughout the years, besides Slovakia. Between 2003 and 2004, energy recovery from municipal waste dramatically increased in Austria. In 2018, Austria recovered the most energy from municipal waste and Slovakia recovered the least amounts of energy. Czech Republic, Slovakia, and Poland have consistently recovered less energy from municipal waste than the EU28 average. Starting in 2009, Germany has recovered more energy from municipal waste than the EU28 average.

[6] Data is missing for Czech Republic from 1995 to 1997. The recycling of materials is defined as, "…any recovery operation by which waste materials are reprocessed into products, materials or substances whether for the original or other purposes." (Eurostat, 2021)

1.5.5 Recycled Municipal Waste of Materials[7]

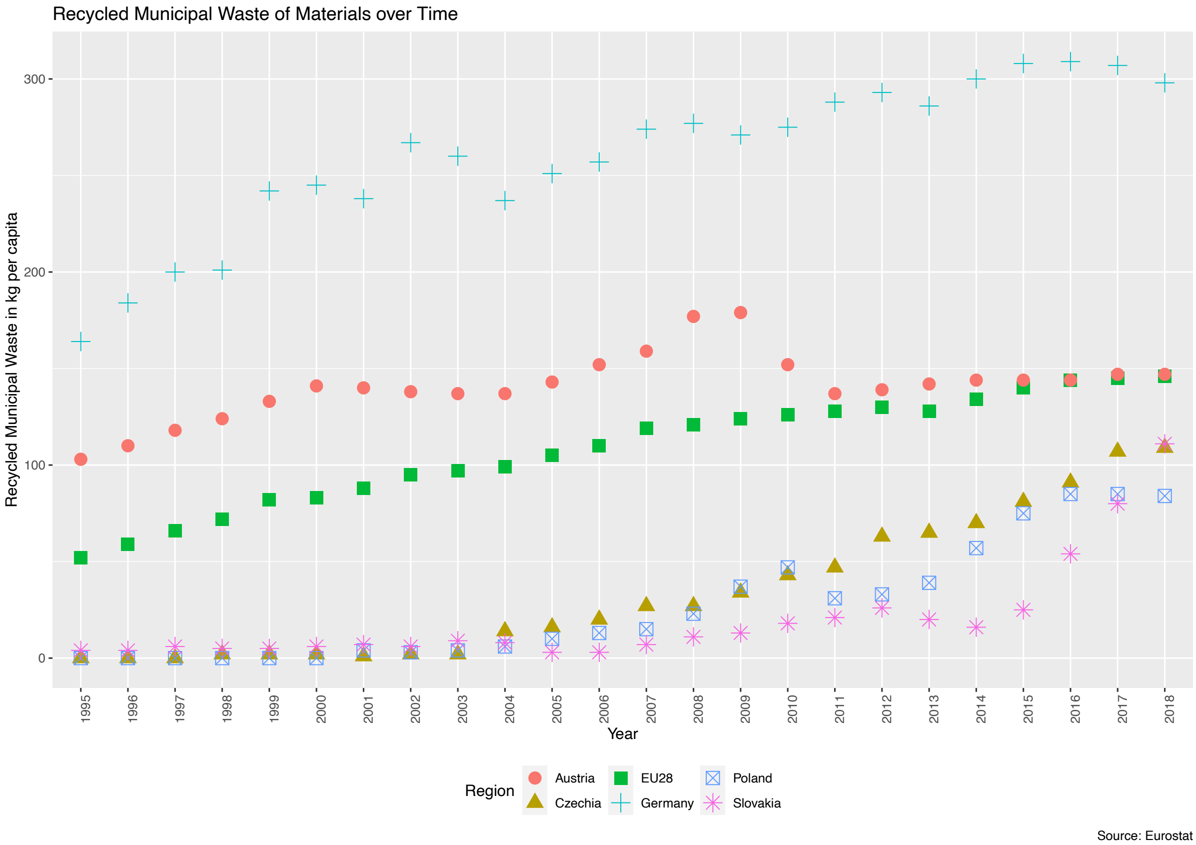


Figure 5: Scatterplot of Recycled Municipal Waste of Materials over Time for Selected countries (1995 - 2018)

Figure 5 shows the recycling of materials in municipal waste over time from 1995 to 2018. For all countries, the recycling of material increased throughout the years. The recycling of materials in Austria decreased between the years of 2009 and 2011 and then slowly increased again. Overall, Germany and Austria are both above the EU28 in the recycling of materials. Czech Republic, Poland, and Slovakia are below the EU28 average in the recycling of materials.

In 2018, Germany recycled the most material municipal waste, and Poland recycled the least material municipal waste. It is also worth noting the steep increase in the recycling of materials for Slovakia between 2014 to 2018.

1.6 Results

The results section is divided into three subsections based on three different municipal waste indicators. The municipal waste indicators are total municipal waste, landfilled municipal waste, and recycling of materials in municipal waste. Due to data availability, the countries and the years examined will be listed in each subsection.

For each subsection, 12 panel regressions will be presented. To find the best model available for each panel, I have devised three criteria for eliminating models that are not suitable. The first criterion looks at the overall model and coefficient significance. The second criterion focuses on comparing models, e.g., time effects vs no time effects. The third criterion focuses on other modelling problems such as serial correlation and cross-sectional dependence. This chapter will use a 5% significance level. R codes used in this chapter are included in the appendix.[8]

[7] Data is missing for Czech Republic from 1995 to 1997.
[8] The R codes are adapted from the tutorial written by Oscar Torres-Reyna (2010).

Table 1: Descriptive Statistics of Final Consumption Expenditure of Households

	Minimum	Median	Mean	Maximum
Final Consumption Expenditure of Households (PPS per capita)	2960.00	12880.00	12673.00	24900.00

Source: Eurostat
Note: these are not naturally logged values

The minimum final consumption expenditure of households is 2960 PPS per capita, which was Estonia in 1995. The maximum final consumption expenditure of households is 24900 PPS per capita, which was Switzerland in 2015. The median final consumption expenditure of households is 12880 PPS per capita, which was Slovenia in 2016, and the average final consumption expenditure of households is 12673 PPS per capita across all countries and years.

1.6.1 Total Municipal Waste

1.6.1.1 Descriptive Statistics

The panel for examining total municipal waste and final consumption expenditure of households contains 29 countries and dates from 1995 to 2018. The countries examined in this panel are Austria, Belgium, Bulgaria, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom.

Table 2: Descriptive Statistics of Total Municipal Waste

	Minimum	Median	Mean	Maximum
Total Municipal Waste (kg per capita)	239.00	495.00	504.80	862.00

Source: Eurostat
Note: these are not naturally logged values

The minimum total municipal waste generated is 239 kilograms per capita, which was Slovakia in 2001. The maximum total municipal waste generated is 862 kilograms per capita, which was Denmark in 2011. The average total municipal waste generated across all countries and years is 504.8 kilograms per capita, and the median total municipal waste generated across all countries and years is 495 kilograms per capita.

Figure 6: Scatterplot of Total Municipal Waste vs Final Consumption Expenditure of Households

Figure 6 shows the scatterplot between total municipal waste and final consumption expenditure of households. As we can see from the graph, the relationship between the two variables are unclear. The left half of the graph shows almost no relationship between the independent and the dependent variable, while the right half of the graph shows a positive relationship between the two variables. The three green dots clustering together on the top right corner is Luxembourg.

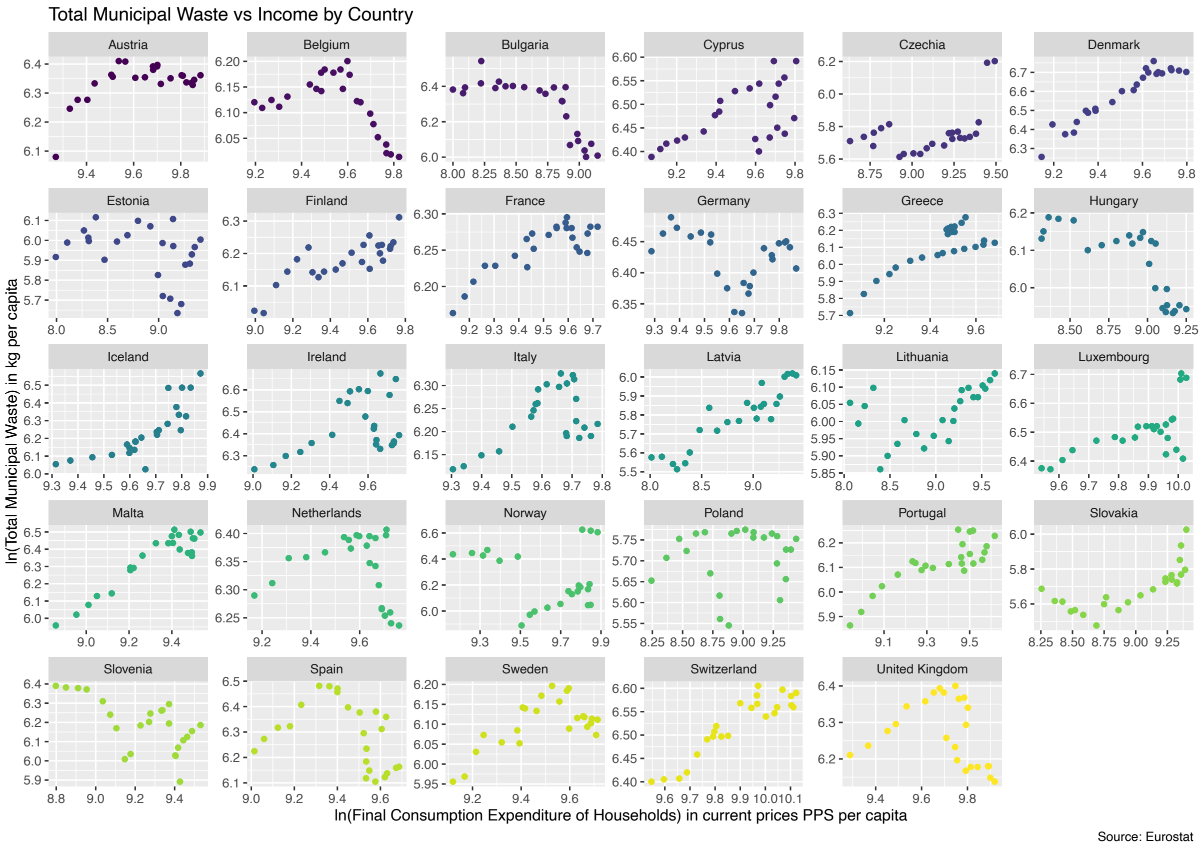


Figure 7: Scatterplot of Total Municipal Waste vs Final Consumption Expenditure of Households by Country

Figure 7 shows the scatterplot of total municipal waste with final consumption expenditure of households by country. From this graph, we can see that for each country, the relationship between the two variables are rather different. For some countries, the relationship seems to be linear, e.g., Denmark and Iceland. For some countries, the relationship seems to be parabolic, e.g., Belgium and Spain. For some other countries, the relationship is rather ambiguous, e.g., Poland and Norway.

1.6.1.2 Panel Results

Table 3: Panel Regression Results for Total Municipal Waste

	Model	FCEH	FCEH^2	FCEH^3	Shape
1	Fixed Effects	0.097913* (0.056802)	-	-	Positive Linear
2	Fixed Effects	-1.943342* (1.134769)	0.112681* (0.061487)	-	U shape
3	Fixed Effects	-17.960654 (20.811231)	1.881972 (2.294427)	-0.064998 (0.084142)	Mirrored N shape
4	Random Effects	0.108814* (0.056957)	-	-	Positive Linear
5	Random Effects	-2.049781* (1.136574)	0.119093* (0.061536)	-	U shape
6	Random Effects	-18.541186 (20.756114)	1.940452 (2.288814)	-0.066899 (0.083959)	Mirrored N shape
7	Time Fixed Effects	0.0061387 (0.1255692)	-	-	Positive Linear

8	Time Fixed Effects	-2.9928563* (1.5387253)	0.1768079** (0.0892253)	-	U shape
9	Time Fixed Effects	-18.328488 (21.362632)	1.876256 (2.374057)	-0.062694 (0.088030)	Mirrored N shape
10	Time Random Effects	0.0708785 (0.1162888)	-	-	Positive Linear
11	Time Random Effects	-3.4342419*** (1.3284606)	0.2043423*** (0.0755015)	-	U shape
12	Time Random Effects	-1.7194e+01 (2.1038e+01)	1.7273 (2.3314)	-5.6093e-02 (8.6136e-02)	Mirrored N shape

Note: N = 696. - means unavailable. Round brackets indicate robust standard errors. All coefficients are estimated using sandwich estimators.
*** indicates 99% significance or above. ** indicates 95% significance. * indicates 90% significance.

Table 2 presents all regression results between total municipal waste and final consumption expenditure of households. The Lagrange Multiplier test indicates that there is a panel effect in the data, thus the use of pooled OLS is not appropriate. The F test indicates that there is a time effect in the data, thus time is an important factor when considering between models. The Augmented Dickey-Fuller test shows that the panel is stationary.

By using the first and second criteria, models 8 and 11 are left. The Hausman test indicates that random effects are more appropriate. The Breusch-Godfrey/Wooldridge test shows that both models exhibit serial correlation and the Breusch-Pagan test confirm that both models exhibit heteroskedasticity. The Pesaran CD test shows that the models are not cross-sectional dependent. Serial correlation and heteroskedasticity are treated by using robust standard errors. With all tests above, model 11 is the preferred model.

Model 11 is a random effects model with time effects, describing a positive quadratic relationship between total municipal waste and final consumption expenditure of households. The adjusted R-squared value for model 11 is 15.6%, which means that only 15.6% of the total variation in the data is explained by this model. It is worth nothing that the positive quadratic relationship do not corroborate with previous literature.

1.6.2 Landfilled Municipal Waste

1.6.2.1 Descriptive Statistics

The panel for examining landfilled municipal waste and final consumption expenditure of households contains 29 countries and dates from 1995 to 2018. The countries examined in this panel are Austria, Belgium, Bulgaria, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom.

Table 4: Descriptive Statistics of Landfilled Municipal Waste

	Minimum	Median	Mean	Maximum
Landfilled Municipal Waste (kg per capita)	0.00	234.00	235.50	675.50

Source: Eurostat
Note: these are not naturally logged values

The average landfilled municipal waste is 235.5 kilograms per capita across all countries and years examined. The median landfilled municipal waste is 234 kilograms per capita across all countries and years examined. The country with the highest landfilled municipal waste is Cyprus in 2008, with 675.5 kilograms per capita. The country with the lowest landfilled municipal waste is Switzerland from 2004 to 2018, with 0 kilograms per capita.

Figure 8: Scatterplot of Landfilled Municipal Waste vs Final Consumption Expenditure of Households

Figure 8 illustrates the scatterplot between final consumption expenditure of household and landfilled municipal waste. In general, the relationship between the two variables are unclear. In the left half of the graph, the two variables seems to be in constant of each other. In the right half of the graph, we can see that the two variables seem to have a negative relationship with each other.

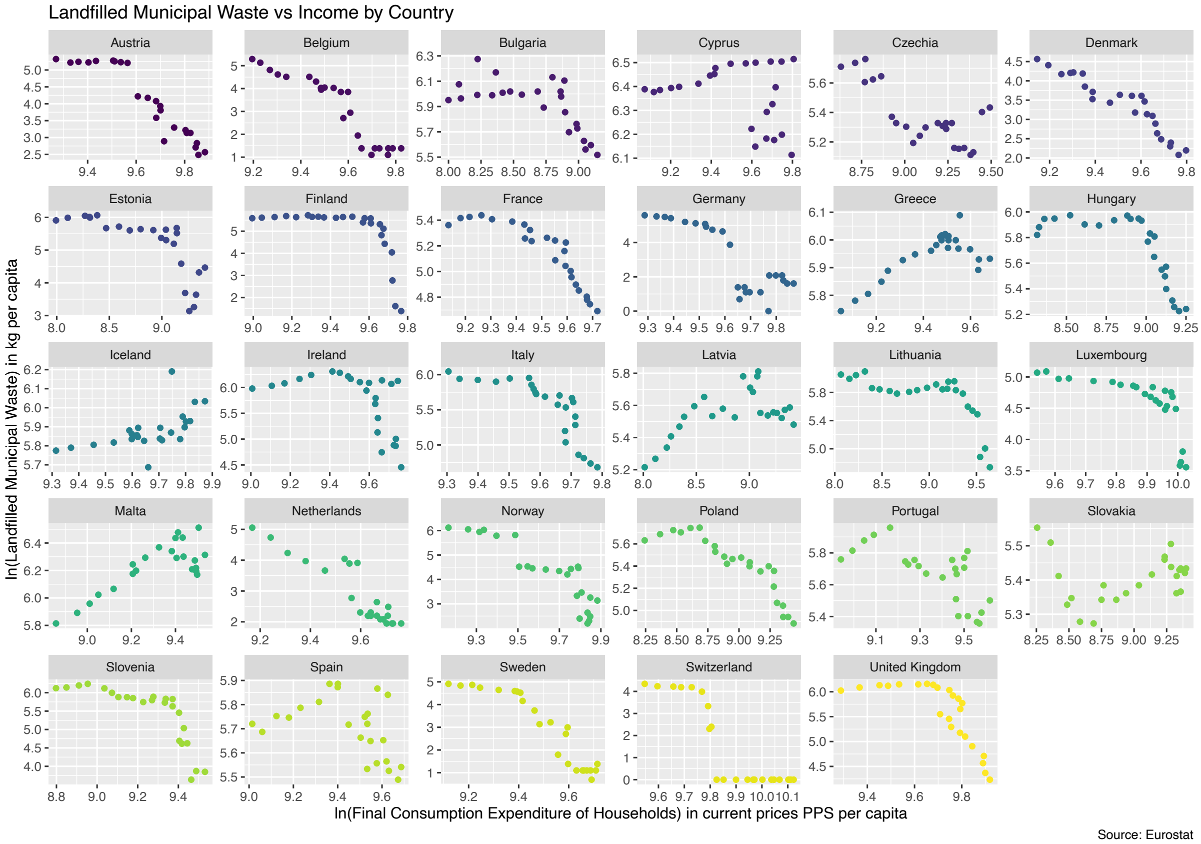


Figure 9: Scatterplot of Landfilled Municipal Waste vs Final Consumption Expenditure of Households by Country

Figure 9 shows the various scatterplots between final consumption expenditure of households and landfilled municipal waste by country. Across all countries, the shape of the relationship is rather different. In general, there are more countries that exhibit a negative relationship than a positive relationship between the two variables. However, there are also countries that exhibit ambiguous relationships, such as Cyprus.

1.6.2.2 Panel Results

Table 5: Panel Regression Results for Landfilled Municipal Waste

	Model	FCEH	FCEH^2	FCEH^3	Shape
13	Fixed Effects	-1.56331*** (0.39881)	-	-	Negative Linear
14	Fixed Effects	36.17631*** (7.71442)	-2.08330*** (0.43307)	-	Inverse U shape
15	Fixed Effects	-423.20631*** (111.90804)	48.66064*** (12.52894)	-1.86417*** (0.46682)	Mirrored N shape
16	Random Effects	-1.57054*** (0.39616)	-	-	Negative Linear
17	Random Effects	36.16151*** (7.75772)	-2.08197*** (0.43551)	-	Inverse U shape
18	Random Effects	-423.31085*** (113.87877)	48.66825*** (12.74927)	-1.86428*** (0.47503)	Mirrored N shape
19	Time Fixed Effects	1.359040* (0.694280)	-	-	Positive Linear
20	Time Fixed Effects	25.439038*** (7.021434)	-1.419654*** (0.398619)	-	Inverse U shape

21	Time Fixed Effects	-414.18*** (113.42)	47.297*** (12.701)	-1.7972*** (0.47336)	Mirrored N shape
22	Time Random Effects	0.976717* (0.547705)	-	-	Positive Linear
23	Time Random Effects	27.431529*** (7.352302)	-1.543502*** (0.412744)	-	Inverse U shape
24	Time Random Effects	-417.82*** (115.95)	47.747*** (12.999)	-1.8161*** (0.48510)	Mirrored N shape

Note: N = 696. - means unavailable. Round brackets indicate robust standard errors. All coefficients are estimated using sandwich estimators.
*** indicates 99% significance or above. ** indicates 95% significance. * indicates 90% significance.

Almost all models regressed with this panel are statistically significant at the five percent level. The Lagrange-Multiplier test indicates that there is a panel effect in the data, thus the use of pooled OLS is not recommended. The Lagrange multiplier test for time effects and the F test both show that there is a time effect in the data. This means that time is an important factor. The Augmented Dickey-Fuller test suggests that the panel is stationary.

By using the first and second criteria, models 20, 21, 23, and 24 are left. The Breusch-Pagan test indicates that there is heteroskedasticity, which is solved by using robust standard errors. The Pesaran CD test shows that all models do not suffer from cross-sectional dependence. The Breusch-Godfrey/Wooldridge test shows that all models have serial correlation which is rectified by using robust standard errors. The Hausman test shows that random effects are better in mapping the relationship. Using all of the results above, models 23 and 24 are left.

Model 23 is a random effects model with time effects, modelling a negative quadratic relationship between landfilled municipal waste and final consumption expenditure of household. Model 24 is a random effects model with time effects, modelling a negative cubic relationship between landfilled municipal waste and final consumption expenditure of household. The adjusted R-squared value for model 23 is 45.4%, and the adjusted R-squared value for model 24 is 50.3%. Both models are statistically significant. With both models rather similar, but wildly different in its implications, it is unclear as to which model is better.

1.6.3 Recycled Materials of Municipal Waste

1.6.3.1 Descriptive Statistics

The panel for examining recycled materials of municipal waste and final consumption expenditure of households contains 26 countries and dates from 2002 to 2018. The countries examined in this panel are Austria, Belgium, Bulgaria, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and United Kingdom.

Table 6: Descriptive Statistics of Recycled Materials of Municipal Waste

	Minimum	**Median**	**Mean**	**Maximum**
Recycled Materials of Municipal Waste	2.00	111.50	116.90	309.00

(kg per capita)				

Source: Eurostat
Note: these are not naturally logged values

The country with the lowest recycled materials of municipal waste is Czechia in 2002, with 2 kilograms per capita. The country with the highest recycled materials of municipal is Germany in 2016, with 309 kilograms per capita. The median recycled materials of municipal waste is 111.5 kilograms per capita across countries and years, and the average recycled materials of municipal waste is 116.9 kilograms per capita.

Figure 10: Scatterplot of Recycled Materials of Municipal Waste vs Final Consumption Expenditure of Households

Figure 10 shows the scatterplot between final consumption expenditure of households and recycled materials of municipal waste. As we can see, there is generally a positive relation between the two variables, however the relationship displayed in figure 10 is rather ambiguous. In the left half of the figure, it is unclear what kind of relationship it is between the two variables. In the right half of the figure, we can see that the two variables do seem to have a positive relation.

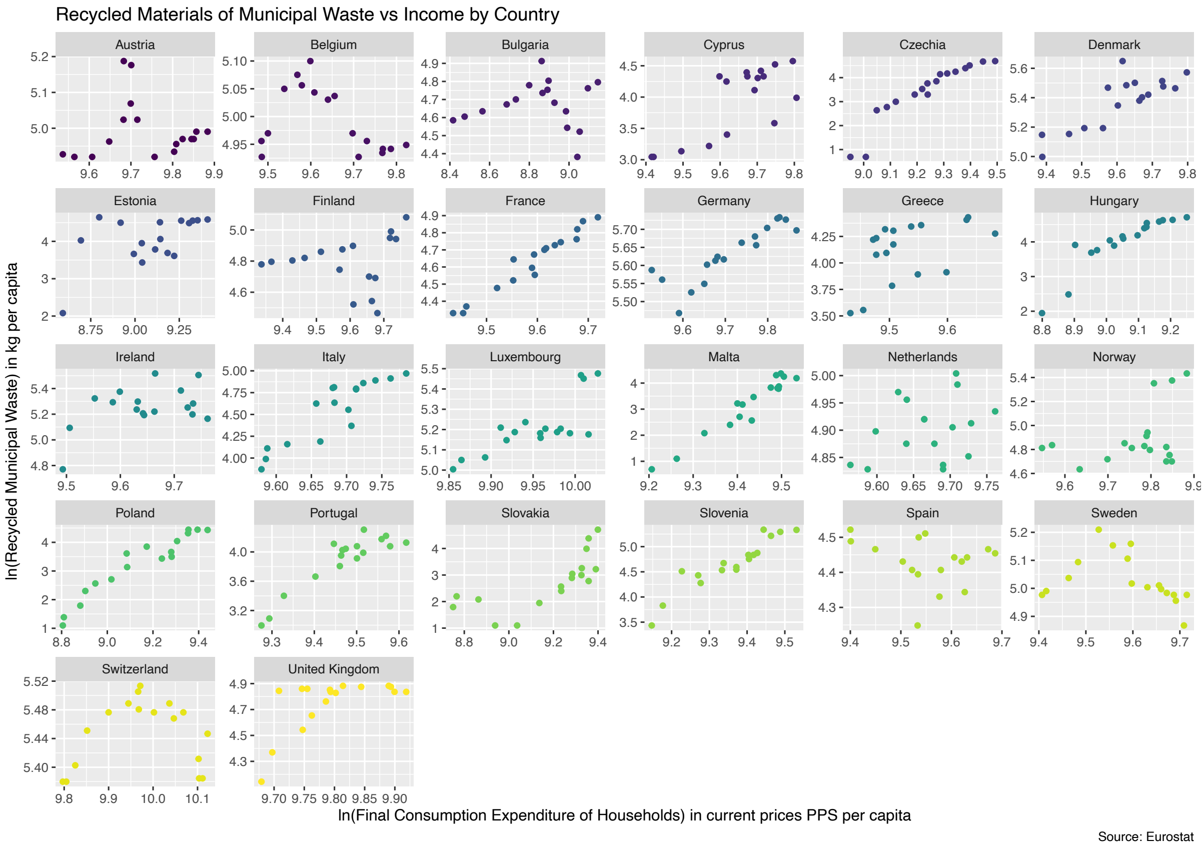


Figure 11: Scatterplot of Recycled Materials of Municipal Waste vs Final Consumption Expenditure of Households by Country

Figure 11 shows different plots of recycled waste with household expenditures by country. The relationship between the two variables largely varies with each country, and there is no general image of how the relationship is. Some countries display a positive linear trend, e.g. France and Malta, but some countries display a hazy relation, e.g. Netherlands and Spain.

1.6.3.2 Panel Results

Table 7: Regression Results for Recycled Materials of Municipal Waste

	Model	FCEH	FCEH^2	FCEH^3	Shape
25	Fixed Effects	2.5518*** 0.5750	-	-	Positive Linear
26	Fixed Effects	14.75637 16.97094	-0.65735 0.89387	-	Inverse U shape
27	Fixed Effects	-995.9969*** 269.9445	108.2559*** 29.2389	-3.9063*** 1.0536	Mirrored N shape
28	Random Effects	2.44789*** 0.55534	-	-	Positive Linear
29	Random Effects	13.59421 16.51801	-0.59968 0.86648	-	Inverse U shape
30	Random Effects	-934.1888*** 258.4802	101.4888*** 27.9989	-3.6603*** 1.0090	Mirrored N shape
31	Time Fixed Effects	1.957898** 0.877454	-	-	Positive Linear
32	Time Fixed Effects	23.941044 19.415141	-1.224329 1.037330	-	Inverse U shape

33	Time Fixed Effects	-1017.6*** 295.91	111.06*** 32.121	-4.0295*** 1.1612	Mirrored N shape
34	Time Random Effects	1.866839** 0.726927	-	-	Positive Linear
35	Time Random Effects	18.605196 17.248185	-0.915867 0.906174	-	Inverse U shape
36	Time Random Effects	-975.77568*** 276.819836	106.240023*** 30.038873	-3.844199*** 1.085494	Mirrored N shape

Note: N = 696. - means unavailable. Round brackets indicate robust standard errors. All coefficients are estimated using sandwich estimators.
*** indicates 99% significance or above. ** indicates 95% significance. * indicates 90% significance.

Table 7 contains all regression results for this panel. The Lagrange Multiplier test shows that there is a panel effect in the data, thus the use of pooled OLS is not recommended. The F test for time effects indicates that there is a time effect in the model. This means that time is an important factor. The Augmented Dickey-Fuller test shows that the series is stationary.

After applying criteria one and two, model 31, 33, 34, and 36 are left. When comparing between model 34 and 31, the Hausman test indicates that the random effects model (model 34) is better. However, when comparing between models 36 and 33, the Hausman test indicates that the fixed effects model (model 33) is better. The Pesaran CD test shows that all four models do not suffer from cross-sectional dependence. The Breusch-Godfrey/Wooldridge test indicates that all four models are serially correlated. The Breusch-Pagan test shows that heteroskedasticity exists. Heteroskedasticity and serial correlation are treated by using robust standard errors. Taking in consideration of all tests performed above, model 33 and 34 remains.

Model 33 is a fixed effects model with time effects, describing a negative cubic relationship between the two variables. Model 34 is a random effects model with time effects, describing a positive linear relationship between the two variables. The R-squared adjusted value for model 33 is 49.1% and the R-squared adjusted value for model 34 is 38.1%. It is still unclear as to which model better describes the relationship between recycled materials of municipal and final consumption expenditure of households.

1.7 Chapter Discussion and Conclusion

This chapter began with a general introduction to waste, proceeded with an international comparison with neighboring European countries, and ended with an empirical examination on the relationship between municipal waste indicators and final consumption expenditure of households.

Figures 1 to 5 graph the various municipal waste indicators by waste management operations for selected countries through time. Although the total municipal waste has slowly increased over time, there is a trend of moving towards better and more environmentally friendly waste operations such as material recycling and energy recovery. By 2018, most of the selected countries have very low amounts of waste disposal by incineration.

Waste treatment by landfilling is still a concern for Poland, Czech Republic, and Slovakia. According to the latest amendment to the 1999/31/EC directive on waste, the share of landfilled municipal waste should decrease to 10% by 2030 (Bourguignon, 2018). As figure 2 shows, the amount of landfilled waste has decreased for most countries. However, from 2016 to 2018, the amount of landfilled waste increased for Slovakia and Czech Republic. In 2018, 55.31% of total municipal were still landfilled in Slovakia. On top of the high percentage of landfilled waste, illegal waste dumping is a pressing concern in Slovakia (Šedová, 2015).

Based on the results of testing and table 3, model 11 is the preferred model for mapping the relationship between total municipal waste in kilograms per capita and final consumption expenditure of households in PPS per capita. Model 11 is a time random effects model, describing a positive quadratic relationship between total municipal waste and final consumption expenditure of households. This finding minorly conflicts with the results obtained by Mazzanti and Zoboli (2009), where the two authors have only found a positive linear relationship between the two variables. The positive coefficient is unsurprising as previous studies have found that there is no evidence in delinking waste to income. However, the meaning of the squared term poses a great concern. Assuming the existential validity of the model, the squared term implies that municipal waste generation is increasing faster than the results obtained by Mazzanti and Zoboli (2009) (keeping in mind that the two authors only examined between 1995 – 2005 with 25 countries, and this panel dates from 1995 – 2018 with 29 countries).

Together with regression results shown in table 5 and several diagnostic tests, model 23 and 24 remains. Both models are random effects models with time effects, with model 23 displaying an inverse U relationship, and model 24 showing a mirrored N relationship between landfilled municipal waste and final consumption expenditure of households. By graphing both regression results against the data, model 24 fits better than model 23, as reflected in the higher adjusted R-squared value.

In the study by Mazzanti and Zoboli (2009), the two authors have found an inverse U relationship between landfilled waste and income. This means that the authors have found the existence of the Environmental Kuznets Curve hypothesis. In EKC literature, finding a cubic relationship between environmental indicators and growth indicators are not surprising (Webber & Allen, 2010). The existence of the negative cubic result does partially corroborate with the Environmental Kuznets Curve hypothesis, such that it proves the latter half of the hypothesis. The negative cubic relationship implies that the change in decreasing landfilled waste in European countries are faster than the previous study by Mazzanti and Zoboli (2009).

Determined from the results of table 7 and several panel diagnostic tests, model 33 and 34 stands out from the rest. Despite having overall statistical significance as well as passing numerous diagnostics, the two models describes two polarizing relationships between the recycling of municipal waste and final consumption expenditure of households. Model 33 describes the relationship between the two variables as negative cubic and model 34 describes the relationship between the two variables as positive linear.

Upon further consultation in existing literature, the negative cubic relationship seems rather unlikely. This doubt is firmly emphasized when the regression results are graphed against the data. Model 33 do not fit the points in the data at all, and model 34 perfectly fits the panel data. This concludes that the relationship between final consumption expenditure of households and recycled materials of municipal waste is positive and linear.

The results of model 34 signifies that an increase in the final consumption expenditure of households leads to an increase in the recycling of materials. The results of this panel do not directly confirm or deny the existence of the Environmental Kuznets Curve hypothesis, but it indirectly verifies the latter half of the hypothesis. Since recycling of materials is not an environmental degradation, but rather an improvement on the environment, and the latter half of the EKC hypothesis states that as income increases, environmental degradation decreases, then the positive linear relationship found in model 34 answers half of the Environmental Kuznets Curve hypothesis.

It is important to note that the downward trend found in landfilled municipal waste and the positive trend found in recycled materials is not simply a matter of increasing in income. The relationship found in both panels are policy induced (Moomaw & Unruh, 1997). The landfill directive sets out clear targets for countries as well as directive on recycled waste (Bourguignon, 2018).

Several limitations exist in this chapter. All of the models regressed suffer from low R-squared values. This means that not all variation within the data are explained by the models. The low R-squared values could also mean that there is omitted variable bias, where insufficient information are provided in the dataset. Another limitation of this chapter is that not all possible effects are examined. Effects such as two-way effects or mixed effects should be examined as well in future research.

Although not within the scope of this chapter, this chapter subtly touched upon policies on municipal waste directives set out by the European Commission. For further research, a further analysis on policy effects should be examined. Another direction for further research could be finding covariates that help better explain the relationship between municipal waste and final consumption expenditure of households. Questions such as "What drives municipal waste generation?" and "What drives municipal recycling?". These questions are rather broad and hard to pin down to the exact causes, but these fundamental questions should be answered in order to further understand the link between municipal waste and income. By answering these questions, better policies could be made on the reduction of waste generation and how to increase recycling.

As a personal hunch, my guess about the driving force in municipal waste generation could be attributed to consumption behavior. As for the drivers in recycling, it could possibly be due to economic incentives, policy or attitudes towards the environment. In a recent study, Zarebska found a high correlation between ignorance and rates of recycling (2014). The author has noted that higher environmental awareness corresponds to better waste management.

This chapter started with a graphical analysis of municipal waste indicators for selected countries, and then explored the relationship between various municipal waste indicators and final consumption expenditure of households. Between total municipal waste and final consumption expenditure of households, a positive quadratic relationship has been found. Between landfilled municipal waste and final consumption expenditure of households, the relationship could either be negative quadratic, which directly confirms the Environmental Kuznets Curve hypothesis or negative cubic, which partially confirms the Environmental Kuznets Curve hypothesis. Between recycled materials of municipal waste and final consumption expenditure of households, a positive linear relationship has been found.

Chapter 2: Packaging Waste in Europe

2.1 Introduction

Almost everything we buy comes with some form of packaging: a soda can, paper bags, or even bubble wrap that comes with your Amazon order. Packaging constitutes a large part of our daily waste, thus a need to analyze it is crucial. This need is even more highlighted when in 2018, the European Union proposed the single use plastic directive, combatting the use of certain plastic packaging. Several countries already have initiatives in place, such as the plastic bag levy in the United Kingdom (Department for Environment, Food, and Rural Affairs UK, 2020).

In 2015, 146 million metric tons of virgin plastic were made solely for the use of packaging in the world, which constitutes almost half of the total virgin plastic generation in that year (Geyer, et al., 2017). In direct comparison, 141 million tons of plastic waste were generated in 2015 (Geyer, et al., 2017). Geyer et al. have also noted that in 2015, only 19.5% of plastic wastes were recycled, and 25.5% of plastics were incinerated, leaving 55% of plastic waste simply discarded (2017).

According to the 94/62/EC of the European Parliament and Council Directive (European Parliament, 2018), packaging is defined as "…all products made of any materials of any nature to be used for the containment, protection, handling, delivery and presentation of goods, from raw materials to processed goods, from the producer to the user or the consumer.". In the same directive, packaging waste is defined as waste that fits the above category of packaging, while excluding production residues (European Parliament, 2018). This broad definition of packaging covers almost all forms of packaging imaginable, such as the bubble wrap used to wrap your delicate glassware to the wooden crate that holds your wine order.

The 94/62/EC directive has also defined the five main categories of packaging waste, namely: plastic, paper and cardboard, metallic, glass, and wooden. Although composite packaging exists, the main waste category is determined by the packaging's most dominant composition (Eurostat, 2020). For example, a soda can is mainly made of metal and a thin layer of plastic, and since its main composition is made of metal, thus it is categorized as a metallic packaging waste.

Packaging waste constitutes 28.1% of total municipal waste generation, according to the Environmental Protection Agency (2021). In 2018, 40.9% of the total packaging waste generated are made of paper and cardboard, and 19% are made of plastic in the EU (Eurostat, 2020). Furthermore, in 2018, only 80.9% of the packaging were recovered, which means that 19.1% of the waste were neither recovered nor recycled (Eurostat, 2020).

Packaging waste is also detrimental to our environment. Studies have shown that wild marine and land animals are suffocating from plastic packaging such as the plastic six-pack beer rings (Gibbens, 2018) or seabirds mistaking plastic waste as a source of food (Perkins, 2016). This mistake is triggered by the scent of plastic after it has been exposed to algae, and thus mimics the smell of a decaying jellyfish (Perkins, 2016). Additionally, plastics could be broken down into microplastics, which is known to be inhaled or ingested through various streams into the human body and is known to be a health concern (Campanale, et al., 2020).

In light of these pressing environmental and health issues, it is imperative to understand more about packaging waste. This chapter will first provide some necessary background information, then examine the evolution of various packaging waste in the EU of selected countries, and then analyze the production of packaging waste using the Environmental Kuznets Curve hypothesis, followed by a discussion and conclusion.

2.2 Aim of the Chapter

The main objective of this chapter is to empirically examine the relationship between income and packaging waste indicators using panel regression, and to test the validity of the Environmental Kuznets Curve hypothesis. All data used in this chapter are sourced from the Eurostat database. This chapter hypothesizes that there is some sort of relationship between packaging waste and income, however, the validity of the EKC is unknown and the exact relationship between income and packaging waste depends on the waste indicator.

2.3 Background

In 2015, the European Union Commission amended the existing packaging waste directive from 1994 (Bonafé, 2019). The new amendment sets out new waste management targets to be met by 2025 and 2030. In particular, the percentage of all packaging waste intended for reuse and recycling must be increased up to 60% in 2025 and 75% in 2030. There are various other targets for specific packaging waste. For plastic packaging, the target for reuse and recycling is set to be 55% for 2025. For paper and cardboard, metal, and glass packaging, the reuse and recycling target for 2025 is 75% and the target for 2030 is 85%. For wooden packaging, the reuse and recycling target for 2025 is 60% and the target for 2030 is 75% (Bourguignon, 2018).

In 2018, paper and cardboard packaging constitutes the largest source of packaging waste in the EU, followed by plastic and glass packaging (Eurostat, 2020). For the panel models, we will be looking at the waste generation of all packaging, paper and cardboard, as well as plastic packaging. By looking at all packaging collectively, we will be able to understand the overall packaging waste generation across countries.

The EU waste directive sets out a waste management hierarchy, listing different types of waste management methods. The list starts with prevention, reuse, recycling, recovery, and then disposal, with prevention being the most favorable course of action and disposal as the least preferred method (European Commission, 2015). Waste recovery includes energy recovery, where the energy from incinerated waste is used to generate heat or electricity (Scarlat, et al., 2018). Disposal methods such as landfilling is least preferred option due to its myriad of potential environmental problems such as the release of greenhouse gas, chemical leakage, negative effects on the local biodiversity, and others (Taylor, 1999).

The Environmental Kuznets Curve is rather dependent on the environmental degradation indicator studied, and cannot be guaranteed to be found in all environmental indicators. (Cavlovic, et al., 2020) (Sarkodie & Strezov, 2019) (Choumert, et al., 2013). To illustrate this, in a study by Azam and Khan, the authors have failed to find the EKC relationship for middle- and high-income countries when examining the relationship between carbon dioxide emissions and income (2016). In another study, Bernard et al. could only confirm the inverse-U relationship for OECD countries in local pollutants (Bernard, et al., 2015). These two studies are a complement of each other since the OECD is made up of high-income countries, and the EKC is only found in local pollutants, and CO2 is a global pollutant.

For EKC studies on comparing waste and income, many authors have found the typical inverse-U relationship. Boubellouta and Sigrid-Brandt examined the relationship between electronic waste generation and income. The authors have found that the typical EKC relationship has been found in 2016 (2021). In a study by Arbulú et al., the authors have found an inverse-U relationship between municipal waste generation and tourism between EU countries, thus confirming the EKC hypothesis (2015).

As Stern (2004) and Van Alstine and Neumayer (2010) have pointed out, the statistical robustness in carrying out empirical EKC studies widely varies and is a point of high concern. The study by Boubellouta and Sigrid-Brandt only examined one point in time and failed to consider the other years. It is also worth pointing out that the two authors examined 2016, even though the biggest importer of electronic waste, China, started the waste import ban in late 2017 (Wen, et al., 2021). The study by Arbulú et al. failed to examine the cubic relationship as suggested by Van Alstine and Neumayer (2010), and in their analysis, the authors have only examined fixed effects, as opposed to other effects as well.

In a study by Mazzanti and Zoboli (2005), the two authors have examined the empirical relationship between packaging waste and GDP per capita[9]. The authors examined the 15 European countries, dating from 1997 to 2001. The authors have concluded that the EKC hypothesis is not empirically found in their study. However, the authors have noted that the lack of the negative quadratic shape is due to weak policy targets (2005).

2.4 Comparing Neighboring Countries

In this section, we will be focusing on selected countries for international comparison. The countries selected for this section are Czech Republic (Czechia), Slovakia (Slovak Republic), Germany, Austria, and Poland, with the EU28 average as a benchmark for cross country comparisons. The countries selected are all neighboring countries of the Czech Republic. The years in this section span from 2005 to 2018. This section focuses on the development of packaging waste indicators over time, with particular interest in all (general) packaging, paper and cardboard packaging, plastic packaging, wood packaging, metallic packaging, and glass packaging. This section is split into subsections of waste operations, such as generation, recycling, and recovery[10], where each subsection will look at the different waste indicators over time.

Missing values are encountered when extracting data from the Eurostat database due to various reasons. If a value is missing between years, then an average of the previous and successive year is used to calculate the missing value. If a value is missing at the ends of a series, then an estimation based on the successive or preceding 5 years are used to calculate the missing value (i.e., a simple regression method is used to calculate the missing value).

[9] I believe this is the only paper published which empirically examine the relationship between packaging waste and income for European countries. Several other papers exist for other kinds of waste.

[10] Waste generation signifies all waste produced. Waste recycling means that the waste is recycled. Waste recovery means that the waste is either recycled or recovered for energy recovery such as the burning of waste to generate heat and electricity. It is important to note that waste generation does not equal to waste recovered, as there are other waste management operations. These other operations include exporting waste elsewhere (Eurostat, 2020).

2.4.1 Packaging Waste Generation

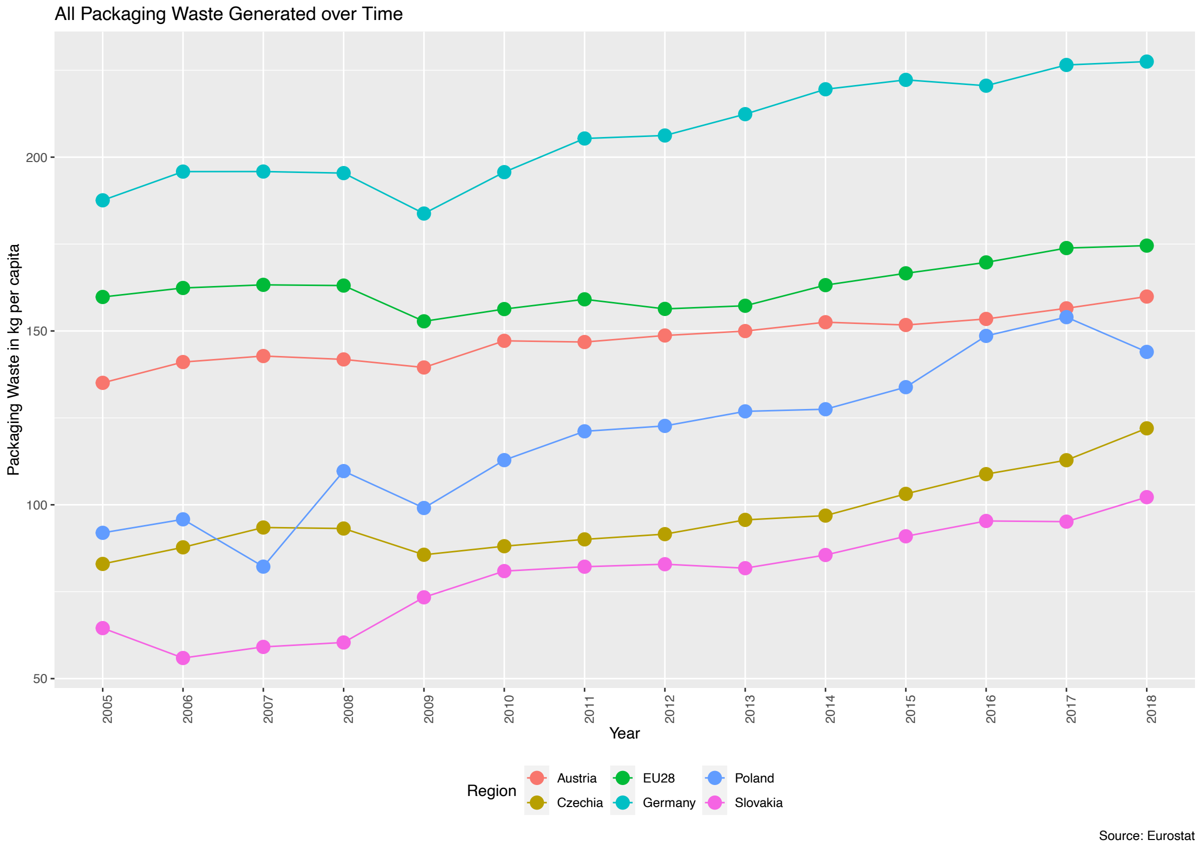


Figure 12: Scatter Line Plot of All Packaging Waste Generated over Time for selected countries (2005 - 2018)

Figure 12 shows the generation of all packaging waste over time. Between the years of 2005 to 2018, there is a steady increase in the generation of packaging waste across all countries. Germany produced more packaging waste than the EU28 average, while other countries included in this comparison are below the EU28 average, with Austria being close to the average. Overall, Slovakia produced the least amount of packaging waste.

It is interesting to note the decrease in packaging waste generation for all countries between the years of 2008 and 2009, except for Slovakia. It is also important to note the fluctuating trend for Poland between the years of 2006 and 2009 and a decrease between the years of 2017 and 2018.

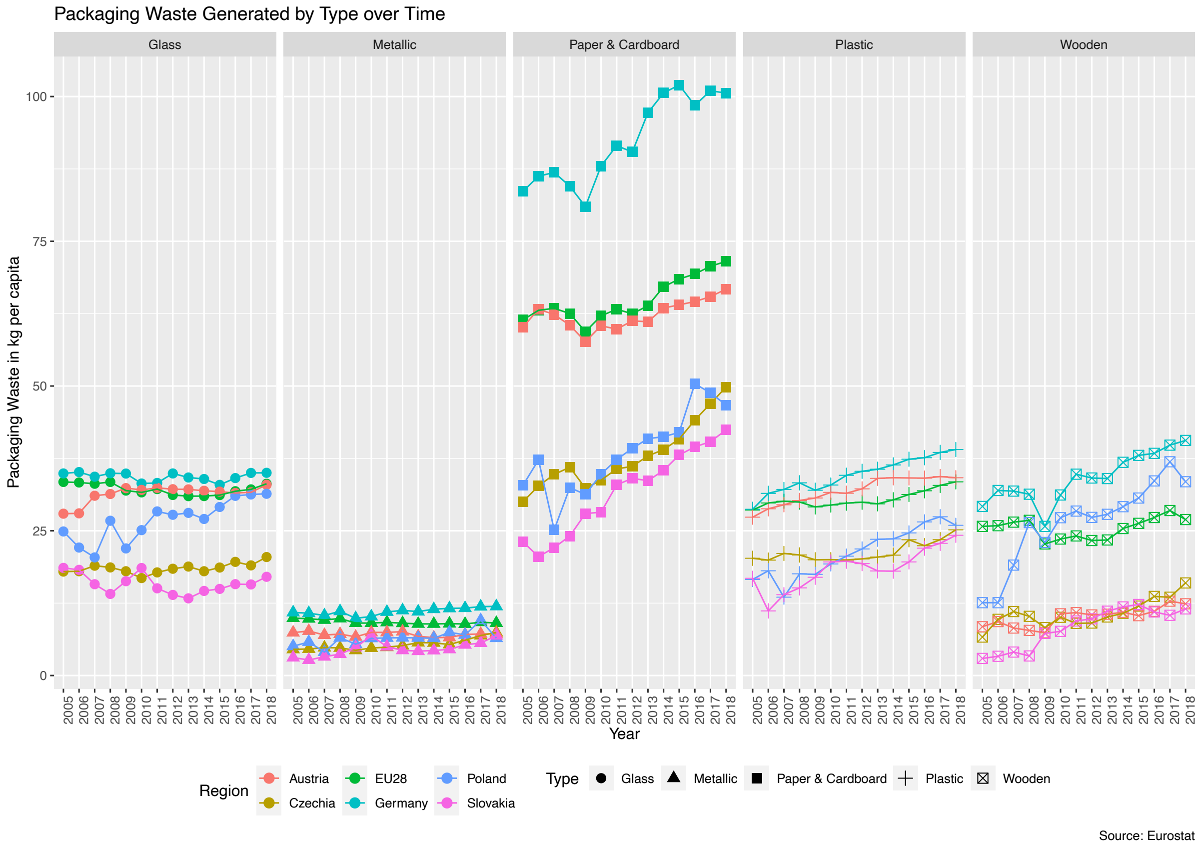


Figure 13: Scatter Line Plot of Packaging Waste Generated by Type over Time for selected countries (2005 - 2018)

Figure 13 shows the generation of packaging waste by type over time. The largest category of packaging waste is paper and carboard. The metallic waste type is the least produced compared to the other categories. For all waste type categories, there is a clear increasing trend over time except for glass and metallic. Across all categories, Germany produces the most packaging waste and Slovakia relatively produces the least packaging waste.

It is interesting to note that Poland surpasses the EU28 average in wooden packaging between the years of 2010 and 2018. Germany consistently surpasses the EU28 average in all types of packaging waste generation, while Czech Republic and Slovakia are below the EU28 average. Poland is generally above the EU28 average in wooden packaging. Austria is generally above the EU28 average in glass and plastic packaging.

It is important to note the large fluctuation in glass packaging between the years of 2005 to 2011 in Poland. This large fluctuation is observed again for Poland in the same years for paper and cardboard, and wooden packaging.

2.4.2 Packaging Waste Recovered

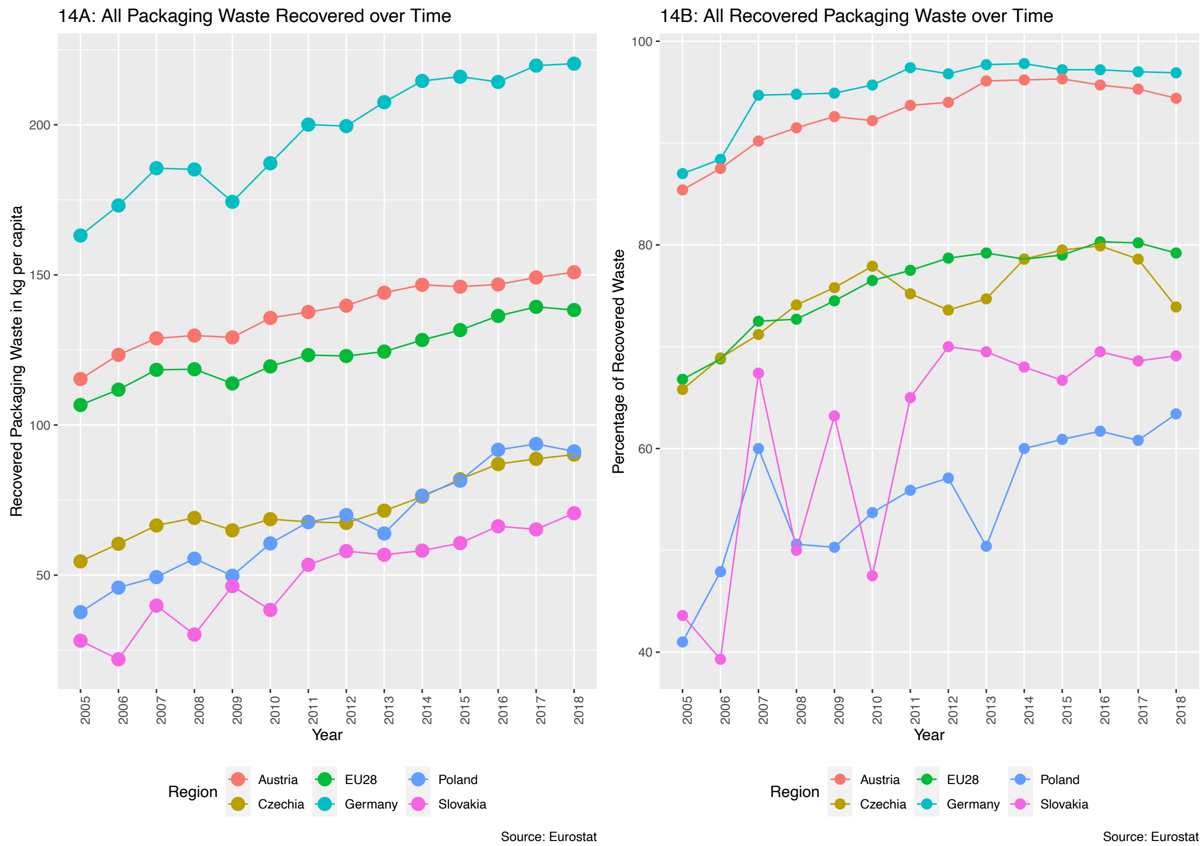


Figure 14: Scatter Line Plot of Recovered Packaging Waste over Time for selected countries (2005 - 2018)

Figure 14A shows the recovered packaging waste over time between the years of 2005 and 2018 in absolute terms. Overall, the graph on the left (14A) shows an increasing trend for all countries during this time period. Germany recovered the most packaging waste compared to other countries and Slovakia recovered the least packaging waste compared to other countries. Both Germany and Austria recovered above the EU28 average throughout 2005 to 2018 in absolute terms. It is interesting to note the fluctuating trend from Slovakia between the years of 2005 to 2011 and the overall decreasing trend for all countries except for Slovakia between the years of 2008 and 2009.

Figure 14B shows the percentage of recovered waste by year and for each country. The percentage is calculated as the total amount of recovered waste divided by the total amount of waste generated (Eurostat, 2020). Germany and Austria recover more of their packaging waste than the EU28 average. It is interesting to note the fluctuating trend for Czechia between the years of 2010 and 2018. Slovakia also displayed a volatile trend between the years of 2005 and 2011.

If we solely look at the year of 2018, Germany and Austria are doing relatively well in terms of packaging waste recovery. Both countries have recovered more than 90% of their packaging waste. Czechia, Poland, and Slovakia should be merited as well with more than 60% of their packaging waste recovered. However, all three countries are still lagging behind in terms of the EU28 average.

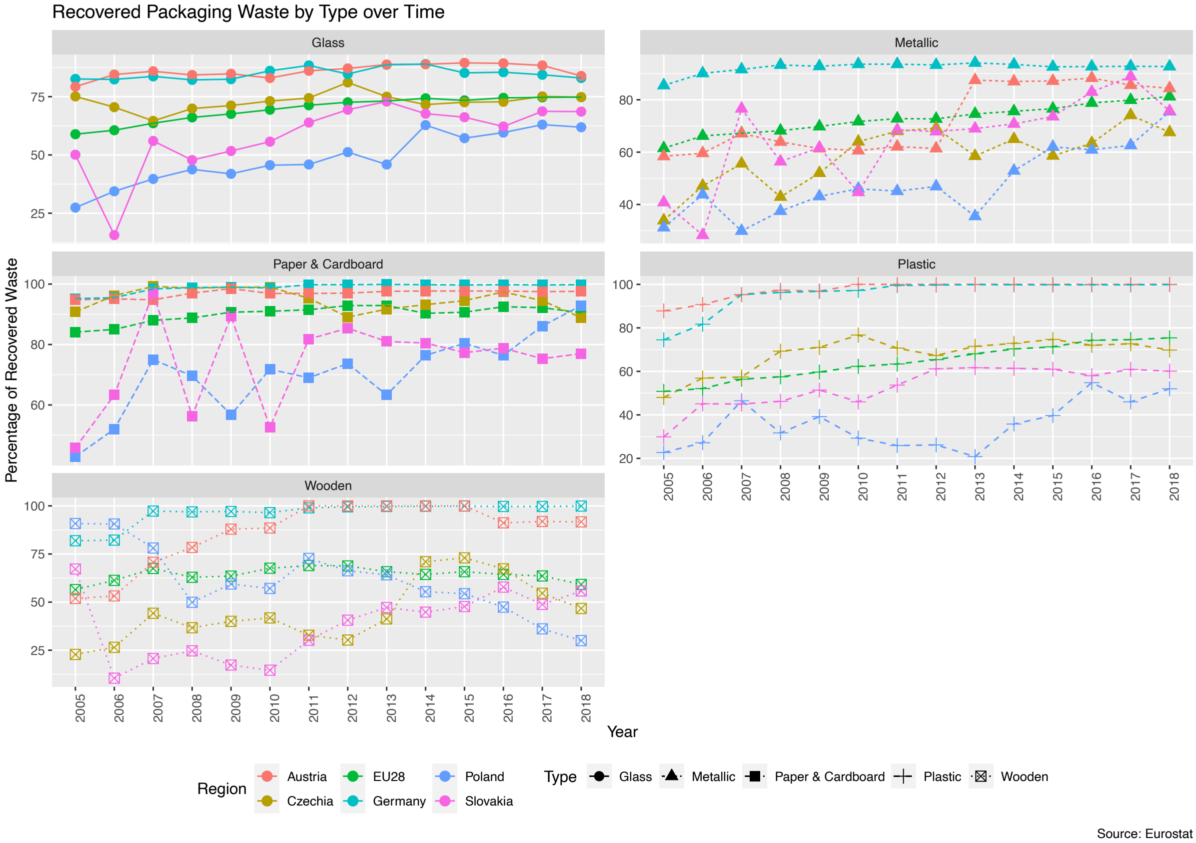


Figure 15: Scatter Line Plot of Recovered Packaging Waste by Type over Time for Selected Countries (2005 - 2018)

Figure 15 shows the recovered packaging waste by type over the years of 2005 to 2018 in percentages. The percentages are calculated from the amount of waste recovered compared to the actual generated packaging waste. Across all waste types, Austria and Germany recovered the most of their packaging waste, with the Czech Republic closely following. Poland shows the most improvement in waste recovery in all categories besides wooden packaging. There is a decreasing trend in the recovery of wooden packaging in Poland between the years of 2005 and 2018.

The recovery rate of packaging waste for Czech Republic is nearly on par with the EU28 average across all types, except for metallic and wooden packaging. It is important to note that from 2011 to 2018, Austria recovered 100% of their plastic waste, and Germany recovered around 97 to 99.8% of their plastic packaging waste.

Slovakia experienced large fluctuations in recovery rates for metallic and paper and cardboard waste between the years of 2005 to 2011.

2.4.3 Packaging Waste Recycled

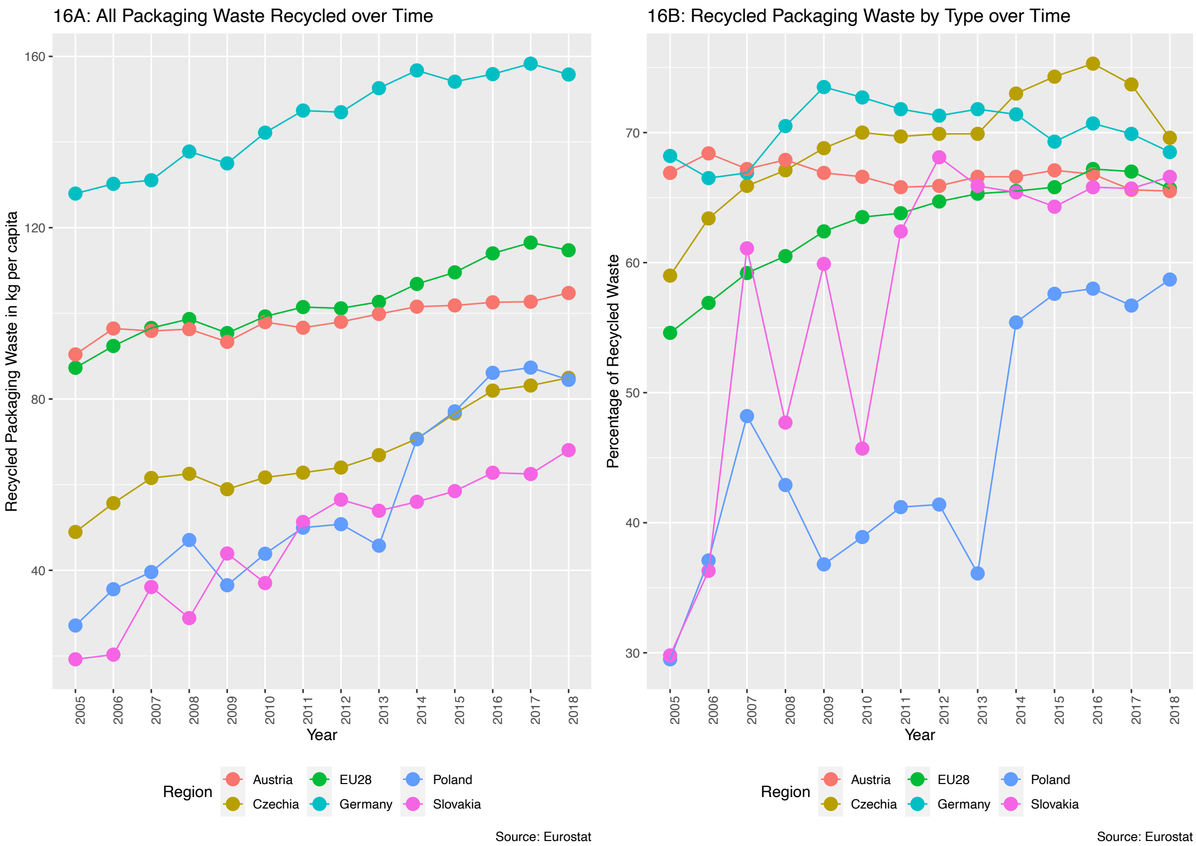


Figure 16: Scatter Line Plot of Recovered Packaging Waste over Time for selected countries (2005 - 2018)

Figure 16A shows the recycled packaging waste by country throughout the years of 2005 to 2018. The graph shows an overall increasing trend for each country over the years. It is interesting to note the fluctuating but increasing trend of packaging recycling in Slovakia between the years of 2006 and 2011. There is a steady increase in Poland between the years of 2008 and 2014. Germany, again, is above the EU28 average.

Figure 16B shows the percentage of recycled waste by country throughout the years of 2005 to 2018. The percentage is calculated as the total amount of waste recycled divided by the total amount of waste generated (Eurostat, 2020). By solely looking at 2018, nearly all countries have a higher recycling rate than the EU28 average except for Poland and Austria. There is a large fluctuation in the recycling rate in Slovakia between the years of 2006 and 2011.

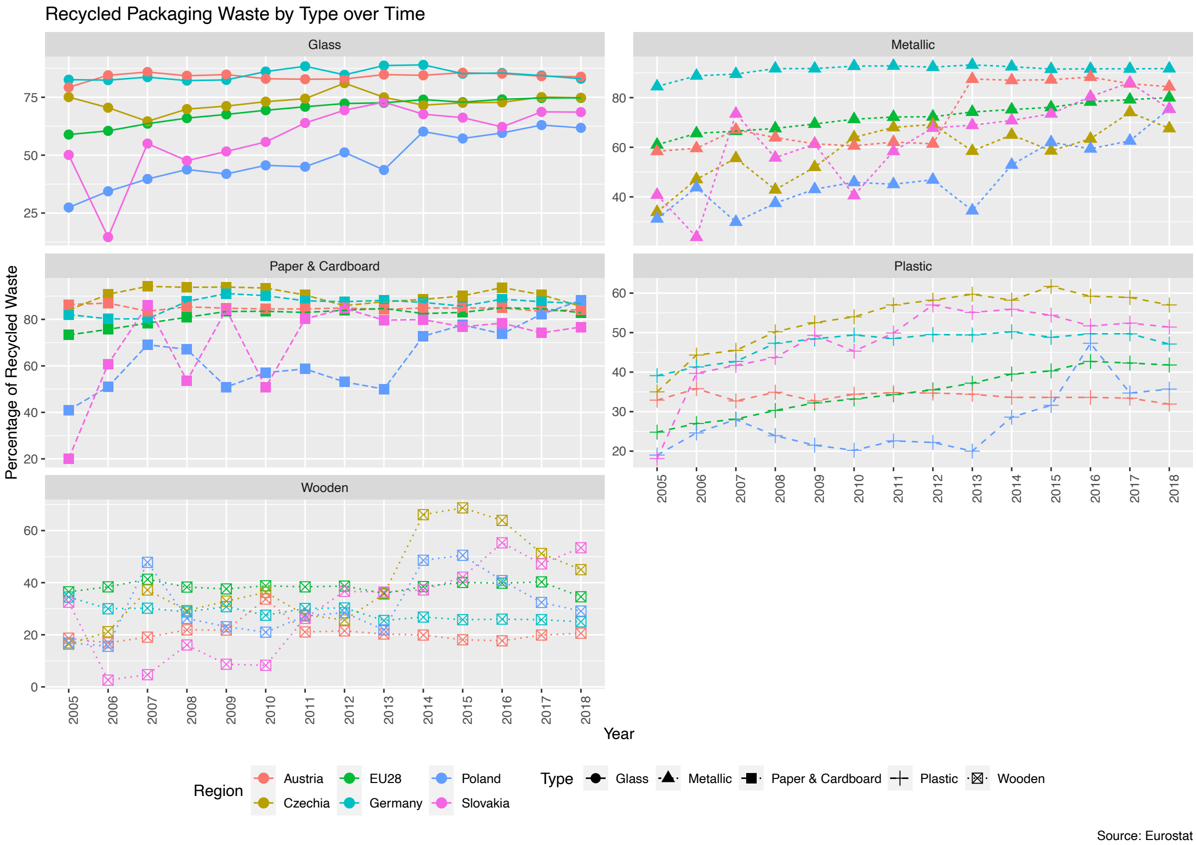


Figure 17: Scatter Line Plot of Recovered Packaging Waste by Type over Time for Selected Countries (2005 - 2018)

Figure 17 shows the recycled packaging waste by the type of packaging for selected countries in percentages. Although recycling is just a part of recovery, the percentages reveal the proportion of recovery that goes through recycling. Overall, the Poland and Slovakia improved the most on recycling of packaging in almost all categories. The recycling rates of each type of waste seems to stabilize over the last few years, especially in glass (2015 – 2018), and paper and cardboard (2014-2018). Metallic and paper and cardboard have the highest rates of recycling across countries in 2018.

2.5 Data and Methods

This chapter is loosely based on the paper by Mazzanti and Zoboli (2005), with recommendations from Van Alstine and Neumayer (2010). Unlike the paper by Mazzanti and Zoboli, this chapter examines a wider selection of countries and a longer time period. This chapter will be adopting specific statistical recommendations from Van Alstine and Neumayer such as the examination of the cubic term as well as examining all effects if possible.

All data used in this chapter are sourced from Eurostat. The dependent variables used in this chapter are total packaging waste generated[11], paper and cardboard packaging waste generated[12], and plastic packaging waste generated[13]. All dependent variables are measured in kilograms per capita. The independent variables are the various degree transformations of

[11] Total packaging waste generated is coded as W1501, with the waste operation of GEN, in the unit of kilograms per capita, under the table code of ENV_WASPAC.
[12] Paper and cardboard packaging waste generated is coded as W150101, with the waste operation of GEN, in the unit of kilograms per capita, under the table code of ENV_WASPAC.
[13] Plastic packaging waste generated is coded as W150102, with the waste operation of GEN, in the unit of kilograms per capita, under the table code of ENV_WASPAC.

Gross Domestic Product in current prices PPS per capita[14], specifically in degrees of 1 to 3. This means that we are examining the linear, quadratic, and cubic relationship between the dependent and independent variables. All variables used in panel regressions are naturally logged. This is to ensure a smoothing of errors in the data, keeping in line with previous research (Mazzanti & Zoboli, 2005), and an easier interpretation of the results.

The following countries are analyzed in the panel regression: Austria, Belgium, Bulgaria, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom. The years examined starts from 2005 and ends in 2018.

A grouping variable to cluster the countries together will be used to help better explain the regional differences (EU Publications Office, 2010). The regional classifications are taken from EuroVoc, which is the official thesaurus used by EU governing bodies (EU Publications Office, 2010).

Adapted from the model used by Mazzanti and Zoboli (2005) and the recommendations from Van Alstine and Neumayer (2010), the base model used in this chapter is presented as follows:

$$W = a + b \cdot Y^3 + c \cdot Y^2 + d \cdot Y + H(t) + G + \varepsilon \qquad [2]$$

From this model, *W* represents the various packaging waste indicators and *a* represents the constant or intercept. *Y* is the Gross Domestic Product in current prices PPS per capita. *H(t)* represents some function of time, G represents the country/region variable, and ε is the error term. Holding *H(t)* and ε constant, the points below discuss the various scenarios in which the model could be interpreted:

- If $b < 0$, and *a*, *c* and *d* are real numbers, then the relationship between packaging waste in kilograms per capita and GDP in current prices PPS per capita is a negative cubic relationship. In other words, an inverted/mirrored N shape.
- If $b > 0$, and *a*, *c* and *d* are real numbers, then the relationship between packaging waste in kilograms per capita and GDP in current prices PPS per capita is a positive cubic relationship. In other words, an N shape.
- If $c < 0$ and $b = 0$, and *a* and *d* are real numbers, then the relationship between packaging waste in kilograms per capita and GDP in current prices PPS per capita is a negative quadratic relationship. In other words, an inverse U shape. This is the shape of the Environmental Kuznets Curve.
- If $c > 0$ and $b = 0$, and *a* and *d* are real numbers, then the relationship between packaging waste in kilograms per capita and GDP in current prices PPS per capita is a positive quadratic relationship. In other words, a U shape.
- If $d < 0$ and $c = b = 0$, and *a* is a real number, then the relationship between packaging waste in kilograms per capita and GDP in current prices PPS per capita is a negative linear relationship. In other words, a negative straight line.
- If $d > 0$ and $c = b = 0$, and *a* is a real number, then the relationship between packaging waste in kilograms per capita and GDP in current prices PPS per capita is a positive linear relationship. In other words, a positive straight line.

[14] This indicator is coded as B1GQ, with the unit measure of CP_PPS_HAB under the table code of NAMA_10_PC in the Eurostat database.

Fixed effects and random effects will both be examined in this chapter. Each packaging waste indicator will be examined under all possible combinations of scenarios using panel regression. All statistical analyses in this chapter are carried out using R[15]. Time effects will also be applied.

2.6 Results

This section is divided into three subsections, with each section focusing on a different packaging waste indicator. The first packaging waste indicator is the total packaging waste generated. The second packaging waste indicator is the paper and cardboard packaging waste generated. The third packaging waste indicator is the plastic packaging waste generated. Each indicator will be introduced with the descriptive statistic and a graph, followed by the different panel models.

In each subsection, around 12 different panel regression models will be presented. In order to select the best model, I have developed a three-step procedure to eliminate models from the best model. The steps are as follows:

1. Statistical significance of coefficients or the overall model.
2. Panel diagnostics such as the Lagrange-Multiplier test or the Augmented Dickey-Fuller test.
3. Further panel diagnostics such as the Breusch-Pagan test, Hausman test, Pesaran CD test, etc.

The first step is to evaluate which model contains statistically significant variables and which model is statistically significant in general. The second step is to ensure if there are no overall problems in the series such as stationarity, time effects, and panel effects. The third step is to test for other problems such as serial correlation, random vs fixed effects, and cross-sectional dependence. This chapter will use the 5% statically significance as the base level.

Table 8: Descriptive Statistics of Gross Domestic Product per capita

	Minimum	Median	Mean	Maximum
Gross Domestic Product in current prices (PPS per capita)	8160.00	25515.00	26928.00	80470.00

Source: Eurostat
Note: these are not naturally logged values

Table 8 shows the descriptive statistics for the independent variable, Gross Domestic Product in current PPS per capita. The country with the lowest GDP per capita is Romania in 2005 with 8160 PPS and the country with the highest GDP per capita is Luxembourg in 2018 with 80470 PPS. The average GDP per capita is 26928 PPS across countries and years. The median GDP per capita is 25515 PPS.

[15] The R codes used in this chapter are adapted from the panel regression manual/tutorial written by Oscar Torres-Reyna (Torres-Reyna, 2010).

2.6.1 Total Packaging Waste Generated

2.6.1.1 Descriptive Statistics

Table 9: Descriptive Statistics of Total Packaging Waste Generated

	Minimum	Median	Mean	Maximum
Total Packaging Waste (kg per capita)	40.33	138.34	137.23	240.63

Source: Eurostat
Note: these are not naturally logged values

Table 9 shows the descriptive statistics of the dependent variable, total packaging waste generated. The country with the highest total packaging waste generated is Ireland in 2006, with 240.63 kilograms per capita. The country with the lowest total packaging waste generated is Bulgaria in 2008, with 40.33 kilograms per capita. The average total packaging waste generated across countries between the years of 2005 to 2018 is 137.23 kilograms per capita. The median total packaging waste generated across countries between the years of 2005 to 2018 is 138.34.

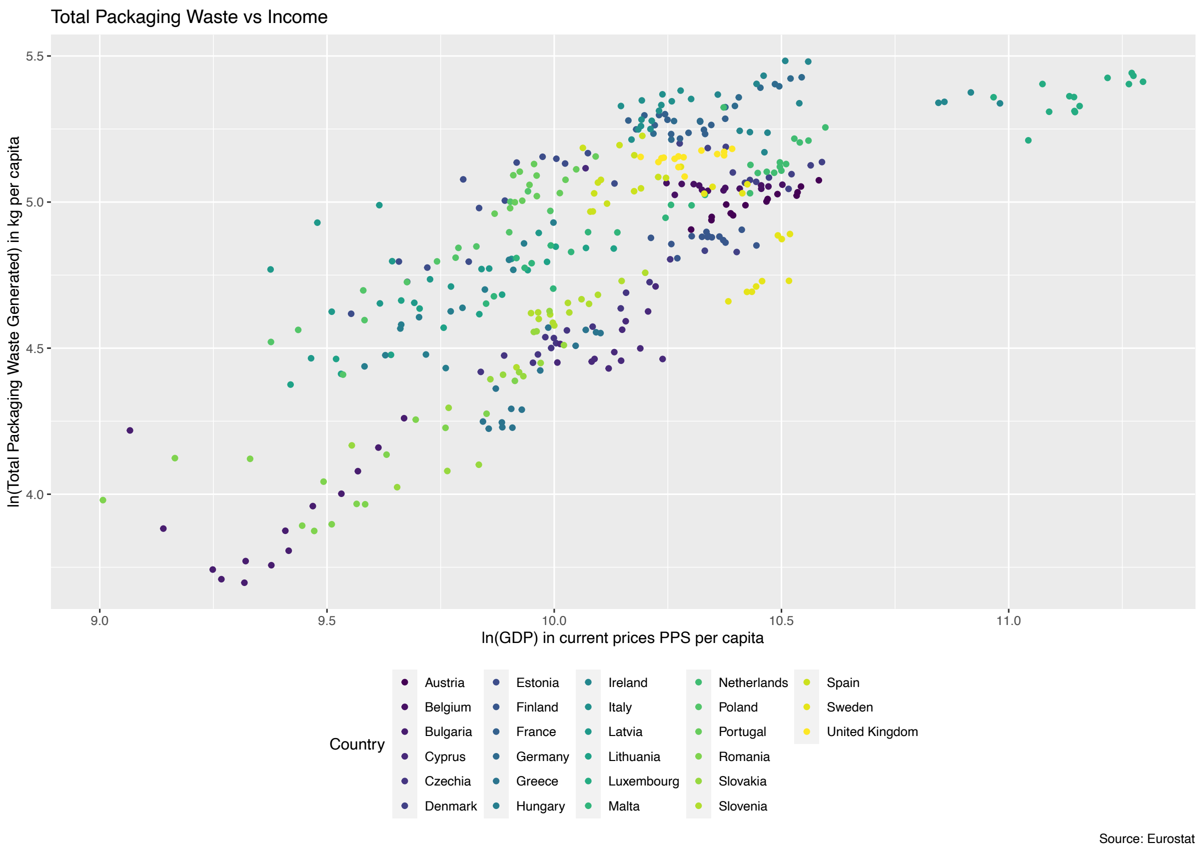


Figure 18: Scatterplot of Total Packaging Waste Generated vs Gross Domestic Product

Figure 18 shows the scatterplot between total generated packaging waste in kilograms per capita and gross domestic product in current prices PPS per capita. As we can see from the graph, it indicates a positive linear trend. There is a cluster on the top right of the graph, which are Luxembourg and Ireland[16], due to their high GDP per capita. The few isolates in the bottom left of the graph are Bulgaria and Romania due to their low GDP, but high packaging waste generation.

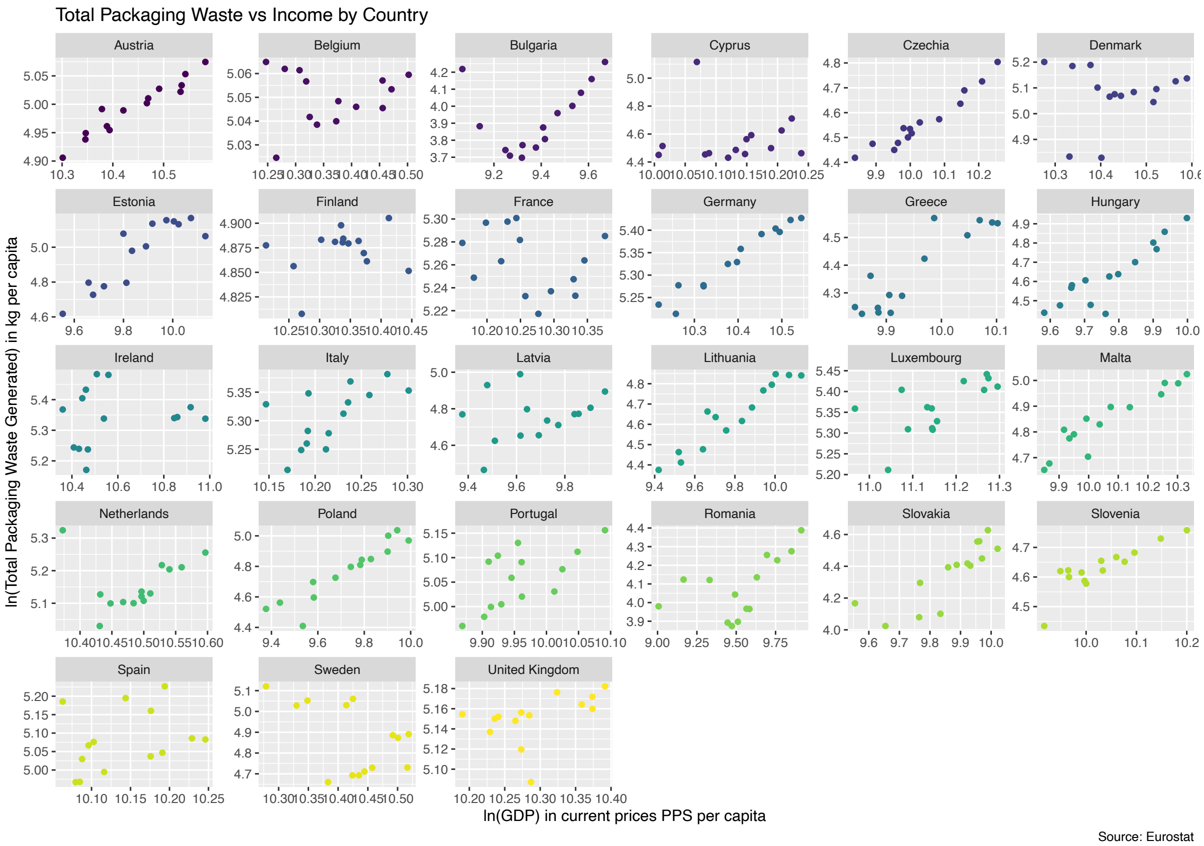


Figure 19: Scatterplot of Total Packaging Waste Generated vs Gross Domestic Product by Country

Figure 19 illustrates the scatterplot of total packaging waste generated and GDP by country. From this picture, not all countries look positively linear. There are countries that display a positive linear trend, for example, Czech Republic, and there are countries that display a rather ambiguous relationship, for example, Sweden and France.

2.6.1.2 Panel Results[17]

Table 10: Panel Regression Results for Total Packaging Waste Generated

	Model	GDP	GDP^2	GDP^3	Shape
1	Fixed Effects	0.547567*** (0.087736)	-	-	Positive Linear
2	Fixed Effects	2.73872 (2.23391)	-0.11026 (0.11146)	-	Inverse U
3	Fixed Effects	-91.01190*** (44.85171)	9.21033*** (4.50497)	-0.30821*** (0.15060)	Mirrored N

[16] The unusually high, "leprechaun economics" of the Irish GDP is mainly due to intellectual properties being moved to Ireland or operational assets being leased to companies in Ireland. For further discussion on this, please see (OECD, 2016).

[17] Only random effects models will include the region variable. Fixed effects models will automatically drop the region variable, even if specified as an effect.

4	Random Effects	0.543258*** (0.083429)	-	-	Positive Linear
5	Random Effects	2.94096 (2.05764)	-0.12047 (0.10233)	-	Inverse U
6	Random Effects	-86.19294*** (42.95755)	8.73228*** (4.30730)	-0.29244*** (0.14374)	Mirrored N
7	Time Fixed Effects	0.758170*** (0.148866)	-	-	Positive Linear
8	Time Fixed Effects	3.289066 (2.539065)	-0.129506 (0.129275)	-	Inverse U
9	Time Fixed Effects	-85.218823* (46.861229)	8.656985* (4.717610)	-0.289981* (0.158097)	Mirrored N
10	Time Random Effects	0.723923*** (0.130052)	-	-	Positive Linear
11	Time Random Effects	3.617622 (2.215723)	-0.147308 (0.111433)	-	Inverse U
12	Time Random Effects	-80.135508* (44.804463)	8.161548* (4.498389)	-0.274031* (0.150296)	Mirrored N

Note: N = 378. - means unavailable. Round brackets indicate robust standard errors. All coefficients are estimated using sandwich estimators.
*** indicates 99% significance or above. ** indicates 95% significance. * indicates 90% significance.

According to the Lagrange Multiplier test, there is a panel effect in the data, which means that the pooled OLS method is not appropriate. The F test for testing time effects indicates that there is a time effect in the data, but the Lagrange Multiplier Breusch-Pagan test indicates otherwise. This means that it is unclear if time is an important factor. The Augmented Dickey-Fuller test indicates that the series is stationary.

By applying the first and second step, only models 1, 3, 4, 6, 7, and 10 are left. Upon further testing, the Hausman test indicates that random effects are more appropriate. This means that only model 4, 6, and 10 are left. The Pesaran CD test shows that there is cross-sectional dependence in models 4 and 6, but not in model 10. Cross-sectional dependence could signify that the results of estimation is biased. The Wooldridge test shows that there is serial correlation in all three models (4, 6, 10), however, this is rectified using robust standard errors. In light of all these additional testing, only model 10 is left.

Model 10 is a random effects model with time effects, estimating the linear relationship between GDP in current prices PPS per capita and total packaging waste generated in kilograms per capita. The adjusted R-squared of the model is 0.4359, which means that 43.59% of the total variation in the data is explained by this model.

2.6.2 Paper and Cardboard Packaging Waste Generated

2.6.2.1 Descriptive Statistics

Table 11: Descriptive Statistics of Paper and Cardboard Packaging Waste Generated

	Minimum	Median	Mean	Maximum
Paper and Cardboard Packaging Waste (kg per capita)	11.62	54.24	53.34	101.99

Source: Eurostat
Note: these are not naturally logged values

The country which generated the least paper and cardboard packaging waste is Bulgaria in 2008, with 11.62 kilograms per capita. The country with the most paper and cardboard packaging waste is Germany in 2015, with 101.99 kilograms per capita. The average of generated paper and cardboard waste across countries and years is 53.34 kilograms per capita. The median of generated paper and cardboard waste across countries and years is 54.24 kilograms per capita.

Figure 20: Scatterplot of Paper and Cardboard Packaging Waste Generated vs Gross Domestic Product

Figure 20 shows the scatterplot between paper and cardboard waste and GDP. As we can see from the graph, there is a clear positive linear relationship between the two variables, if excluding the cluster in the top right corner. The cluster of countries in the top right are Luxembourg and Ireland. The isolate in the most bottom left corner is Romania.

2.6.2.2 Panel Results

Table 12: Panel Regression Results for Paper and Cardboard Packaging Waste Generated

	Model	GDP	GDP^2	GDP^3	Shape

13	Fixed Effects	0.66534*** (0.10282)	-	-	Positive Linear
14	Fixed Effects	2.478444 (2.438307)	-0.091233 (0.123933)	-	Inverse U shape
15	Fixed Effects	-61.49433 (59.41153)	6.26887 (5.98274)	-0.21032 (0.20047)	Mirrored N shape
16	Random Effects	0.665204*** (0.096459)	-	-	Positive Linear
17	Random Effects	3.01400 (2.07916)	-0.11799 (0.10496)	-	Inverse U shape
18	Random Effects	-64.03594 (55.52661)	6.53961 (5.57769)	-0.21987 (0.18641)	Mirrored N shape
19	Time Fixed Effects	0.711483*** (0.139525)	-	-	Positive Linear
20	Time Fixed Effects	3.562461 (2.498039)	-0.145885 (0.128105)	-	Inverse U shape
21	Time Fixed Effects	-48.213770 (61.029144)	4.994125 (6.135973)	-0.169636 (0.205242)	Mirrored N shape
22	Time Random Effects	0.705772*** (0.123376)	-	-	Positive Linear
23	Time Random Effects	4.006647* (2.070653)	-0.167865 (0.104425)	-	Inverse U shape
24	Time Random Effects	-50.662625 (58.230546)	5.254224 (5.839794)	-0.178778 (0.194765)	Mirrored N shape

Note: N = 378. - means unavailable. Round brackets indicate robust standard errors. All coefficients are estimated using sandwich estimators.
*** indicates 99% significance or above. ** indicates 95% significance. * indicates 90% significance.

The Lagrange Multiplier test indicates that there is a panel effect in the data, thus the use of pooled OLS method is not appropriate in this instance. The F test indicates that there is a time effect present, but the Lagrange Multiplier Breusch-Pagan test for time effects indicates otherwise (with a p-value of 0.06, just narrowly missing). This means that time effects could be an important factor. The Augmented Dickey-Fuller test shows that the series is stationary.

After applying steps 1 and 2, only model 13, 16,19, and 22 are left. The Hausman test indicates that random effects are more appropriate, compared to fixed effects. This means that model 13 and 16 are no longer in consideration, leaving us with models 19 and 22. The Pesaran CD test shows that model 16 exhibits cross-sectional dependence and model 22 does not exhibit cross-sectional dependence. The Breusch-Godfrey/Wooldridge test shows that both model 16 and 22 displays serial correlation, which was rectified using robust standard errors. Finally, the Breusch-Pagan test shows that the series is not heteroskedastic. Taking in consideration of all further tests, we can then conclude that model 22 is the preferred model.

Model 22 is a random effects model with time, describing a linear relationship between GDP per capita and paper and cardboard packaging waste . The R-squared adjusted for model 22 is 0.402. This means that 40.2% of the total variation in the data is explained by this model. Conversely, this means that 59.8% of the variation in the data is not explained by this model. The overall model is statistically significant.

2.6.3 Plastic Packaging Waste Generated

2.6.3.1 Descriptive Statistics

Table 13: Descriptive Statistics of Plastic Packaging Waste Generated

	Minimum	**Median**	**Mean**	**Maximum**
Plastic Packaging Waste (kg per capita)	10.37	27.37	28.10	61.75

Source: Eurostat
Note: these are not naturally logged values

The country with the highest generation of plastic packaging waste is Ireland in 2006, with 61.75 kilograms per capita. The country with the lowest generation of plastic packaging waste is Bulgaria, with 10.37 kilograms per capita. The average of generated plastic packaging waste across countries is 28.10 kilograms per capita. The median of generated plastic packaging waste across countries is 27.37 kilograms per capita.

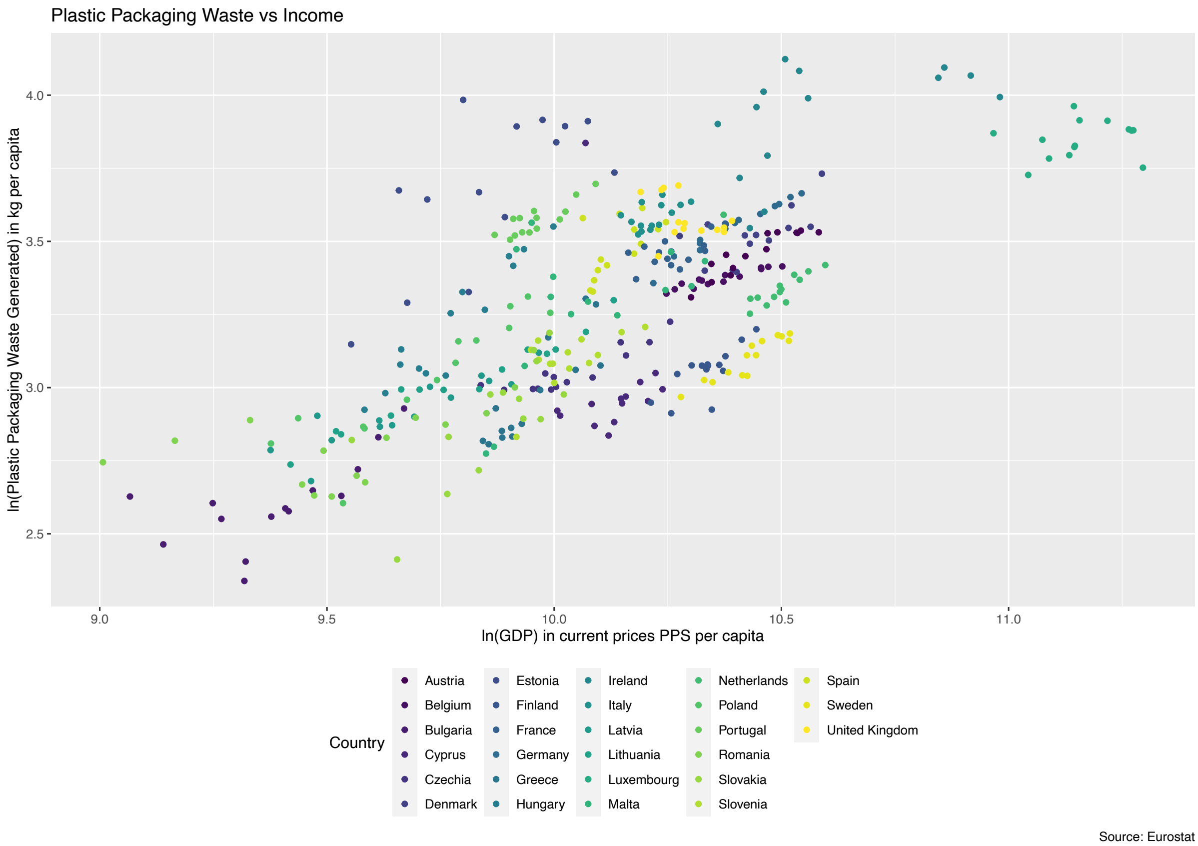


Figure 21: Scatterplot of Plastic Packaging Waste Generated vs Gross Domestic Product

Figure 21 shows the scatterplot between GDP in PPS per capita and plastic packaging waste generated in kilograms per capita. As with the previous graphs (figures 20 and 18), there is a group of countries in the top right corner which consists of Ireland and Luxembourg. Unlike previous graphs, the overall shape is no longer clear cut. As we can see, there is an overall positive trend, but the shape is unclear.

2.6.3.2 Panel Results

Table 14: Panel Regression Results for Plastic Packaging Waste Generated

	Model	GDP	GDP^2	GDP^3	Shape
25	Fixed Effects	0.65890*** (0.08686)	-	-	Positive Linear
26	Fixed Effects	1.132565 (2.287954)	-0.023835 (0.112325)	-	Inverse U shape
27	Fixed Effects	-101.01860*** (29.136331)	10.131925*** (2.881333)	-0.335831*** (0.094836)	Mirrored N shape
28	Random Effects	0.643917*** (0.079877)	-	-	Positive Linear
29	Random Effects	1.339843 (2.149443)	-0.034931 (0.105215)	-	Inverse U shape
30	Random Effects	-93.313587*** (28.192741)	9.365218*** (2.779978)	-0.310495*** (0.091232)	Mirrored N shape
31	Time Fixed Effects	0.790477*** (0.165330)	-	-	Positive Linear
32	Time Fixed Effects	1.167234 (2.335312)	-0.019279 (0.114646)	-	Inverse U shape
33	Time Fixed Effects	-103.50838*** (31.731426)	10.372240*** (3.146150)	-0.342951*** (0.103876)	Mirrored N shape
34	Time Random Effects	0.733314*** (0.141597)	-	-	Positive Linear
35	Time Random Effects	1.607760 (2.109764)	-0.044347 (0.102494)	-	Inverse U shape
36	Time Random Effects	-93.714831*** (29.691357)	9.410847*** (2.931000)	-0.311788*** (0.096309)	Mirrored N shape

Note: N = 378. - means unavailable. Round brackets indicate robust standard errors. All coefficients are estimated using sandwich estimators.
*** indicates 99% significance or above. ** indicates 95% significance. * indicates 90% significance.

The Lagrange Multiplier test indicates that there is a panel effect in the data, thus the use of pooled OLS is not appropriate in this case. The F test and the Lagrange Multiplier Breusch-Pagan test for time effects indicates that there is no time effect. This means that time is not an important factor, but as of now, inconclusive. The Augmented Dickey-Fuller test indicates that the series is stationary.

By using the criteria from steps 1 and 2, several models are left. The Hausman test generally indicates that random effects are more appropriate, but when comparing between model 27 and 30, the test reveals that the fixed effects model (model 27) is preferred. All models left do not display cross-sectional dependence according to the Pesaran CD test. The Breusch-Godfrey/Wooldridge test indicates serial correlation, which was rectified using robust standard errors. According to the Breusch-Pagan test, heteroskedasticity is not present. In light of all further tests, only models 27 and 28 are left.

Model 27 is a fixed effects model showing a negative cubic relationship between plastic packaging waste and GDP. Model 28 is a random effects model showing a positive linear relationship between plastic packaging waste and GDP. The R-squared adjusted for model 27 is 0.365. This means that 36.5% of the total variation in the data is explained by this model. The R-squared adjusted for model 28 is 0.379. This means that 37.9% of the total variation in the data is explained by this model. Both models are statistically significant, and it is inconclusive to indicate which model is better, as both models are extremely similar in test statistics, but wildly different in implications.

2.7 Discussion and Conclusion

This chapter started with a general introduction to the topic of packaging waste, and then descriptively compared the different types of packaging waste by management operations, finishing with an empirical examination on finding the relation between packaging waste indicators and GDP per capita using the Environmental Kuznets Curve hypothesis.

Figures 1 to 6 displays various packaging waste by type as well as by waste management operations through time for selected countries. The graphs show how each indicator evolve through time for each country. A common theme encountered when exploring through these graphs is that Slovakia and Poland displayed fluctuations. The variation for Slovakia stems from the uncertainties in the reporting of waste and statistical issues on calculating waste (Aleksic, 2014). The lower recycling rates in Slovakia in the earlier years of the series is due to high levels of waste being landfilled. The Slovakian Government policy of a landfill tax has been used to address this problem (Aleksic, 2014). Poland also suffers the same high levels of landfill, and the Polish government has addressed this concern by using a landfill tax as well (Fischer, 2013). However, the Polish landfill tax only starting to take effect in 2008. The high variation in the recycling of packaging waste in Poland is due to statistical reporting issues (Fischer, 2013).

Nearly across all countries, packaging waste decreased momentarily between 2008 and 2009. This decrease is due to the global economic crisis (Eurostat, 2020). Apart from this instance, packaging waste generation has been steadily increasing in all countries examined.

Although recycling is one step higher in the waste hierarchy than recovery, recycling rates are still low in certain types of packaging waste (Eurostat, 2020). The recycling of plastic packaging is relatively low compared to other types of packaging waste. This is because different types of plastics cannot be recycled together, thus the process of recycling plastic requires extra processes and resources to do so (Hopewell, et al., 2009).

Based on the results of testing and from table 3, the preferred model for mapping the relationship between total packaging waste generated in kilograms per capita and Gross Domestic Product in current prices PPS per capita is model 10. This means that the relationship between total packaging waste generated and GDP is positively linear. The positive linear relationship means that as GDP increases, total packaging waste generated increases as well. This further implicates that the Environmental Kuznets Curve hypothesis is not empirically found in this instance.

According to the results of table 5 and additional tests, the preferred model for explaining the relationship between paper and cardboard packaging waste and income is model 22. Model 22 describes the relationship between the two indicators as positive and linear. This relationship indicates that as GDP increases, paper and cardboard packaging increases as well. This means that the Environmental Kuznets Curve hypothesis is not empirically found when examining the relationship between paper and cardboard packaging waste and GDP per capita.

The preferred models for explaining the relationship between plastic packaging waste and GDP are models 27 and 28, as per the results of table 7 and additional tests. Model 27 is a negative cubic model relating GDP and plastic packaging waste, and model 28 is a positive linear model relating GDP and plastic packaging waste. Both models are similar in terms of its statistical validity, but have widely different significance. Upon further research in this phenomenon, it is not unusual to find a negative cubic relationship when examining the EKC hypothesis. For instance, Allard et al. found several cubic instances when evaluating between carbon dioxide emissions and GDP (2018). However, based on previous studies, researchers have only found a linear relationship between waste and GDP (Mazzanti & Zoboli, 2005) (Webber & Allen, 2010). It is also important to note that the coefficient for the cubic term in model 27 is rather small and close to zero. When both models are graphed against the data, the cubic model is visibly mistaken. In consideration of the above reasons, model 28 is better in capturing the relationship between plastic packaging waste generated and GDP.

In response to the paper by Mazzanti and Zoboli (2005), this chapter further corroborates with their study and conclude that the relation between GDP and the three packaging waste indicators are linear. Furthermore, this chapter could not empirically prove the Environmental Kuznets Curve hypothesis as well.

The panel regression findings of this chapter are unsurprising. This is because the waste framework directive (European Parliament, 2018) is mainly aimed at the reuse, recycling, and recovery of waste instead of a direct reduction of waste. The reuse of packaging is in effect reducing the overall amount of waste generated however, article 5 of the updated directive is lofty and is only a gentle encouragement for member states of the union to pursue the option of reuse, "Member States may 'encourage' environmentally sound reuse systems…" (The European Organization for Packaging and the Environment, 2021).

Faults and limitations exist in this chapter. Across all models, the R-squared value is relatively low. This means that not all variation in the data is explained and could potentially mean that there could be an omitted variable bias, thus an improvement on the model could be made. Variables such as levels of consumerism, education, and population could potentially help better explain the unexplained variation. This chapter also failed to examine with all possible panel model effects such as the two-way effect or the mixed effects models. For a further study, a more thorough research with all different kinds of methods should be used to further examine the relationship between packaging waste and GDP.

As we have seen from graphs 1 to 6 with the case of the Irish leprechaun economics, GDP could be statistically misleading. For further analysis, an exploration of other income related indicators could be used, such as gross national income. In a different study, a different indicator that measures growth could be used, e.g., the human development index.

In response to the hypothesis set earlier in this chapter, the hypothesis is partially proven. There is a relationship between packaging waste indicators, and this case, all three packaging waste indicators yield the same result of a positive linear relationship with GDP. The Environmental Kuznets Curve hypothesis is not proven in this chapter.

This chapter began with a graphical comparison of packaging waste indicators by waste management and packaging type for selected European countries, and then continued with the empirical examination on the relationship between different generated packaging waste indicators and GDP. This chapter has found a positive linear relationship between total packaging waste generated in kilograms per capita and GDP in current prices PPS per capita. The same positive linear relationship has also been found between paper and cardboard packaging waste and plastic packaging waste with GDP per capita. This chapter does not confirm the Environmental Kuznets Curve hypothesis but can corroborate with previous studies.

Chapter 3: Waste Trade Network

3.1 Introduction and Background

The effects of trade on the environment has always been a constant debate. Proponents of trade suggests that trade encourages better environmental management, such that tax and revenues generated from trade (and inadvertently suggesting economic growth due to trade) could be used for bettering the environment (Bagwati, 1993). As explored in previous chapters, this view between trade and the environment is congruent to the Environmental Kuznets Curve hypothesis. Proponents of trade have also concluded that trade could encourage innovation spill-overs from one country to the other, when tackling with pollution intensive industries (Prakash, 2019).

The main thesis from trade proponents stems from the theory of comparative advantage. According to the comparative advantage in trade theories, countries will specialize in goods and services that they are comparatively better at producing than other countries (Arnold, 2014). However, this theory does not normally take into account external factors such as environmental regulation and policy. Trade proponents argue that since countries will produce goods and services that they are relatively better at, trade encourages a more efficient allocation of resources. The efficient allocation results in a better production and can meet the environmental regulations (Prakash, 2019) (Barrett, 2000). Moreover, technological innovations from a more developed country could be transferred to a less developed country, thus reducing the overall environmental degradation (Dinda, 2004).

Critics who are against trade have often argued with potential environmental externalities such as the tragedy of the commons, pollution havens, race to the bottom, and the displacement hypothesis (Tietenberg & Lewis, 2018). All hypotheses listed above raise potential environmental issues that could arise from trade. For instance, the tragedy of the commons is typical in the fishing industry where everyone has access, but if one disregards the maximum sustainable yield, the population of the fish will soon deplete. As for international trade, the most common critique is that trade encourages a race to the bottom and pollution havens.

The pollution haven hypothesis states that high polluting industries from developed countries will move to developing countries in order to deal with less environmental regulations (Tietenberg & Lewis, 2018). Race to the bottom theorizes that countries (typically developing nations) will compete with each other by lowering environmental standards in order to attract foreign investment and retain its own industries (Tietenberg & Lewis, 2018).

In study by Eliste and Fredjksson (2004), the authors have found that in agricultural trade, the race to the bottom hypothesis do not exist. The authors have also found that countries with similar environmental standards are more likely to trade with each other and there is a positive relation between trade openness and environmental regulations.

In another study by Lucier and Gareau (2015), the authors have found that race to the bottom do exist in the trade of toxic waste by examining the Basel convention. The authors have attributed the race to the bottom with the fact that toxic waste regulations have been coauthored with relevant industries, and have since promoted and rebranded toxic wastes as resources (Lucier & Gareau, 2015). Singh and Mukherjee (2019) has stated that due to the Basel convention[18], the burden of waste imports have shifted to nations that are even worse off than before. This means that waste will be imported by poorer nations, in comparison to prior the agreement from the convention. From the examples above, it seems as if environmental

[18] Even though the Basel convention aimed to promote better waste management around the world (UN Sustainable Development, 2019).

concerns from international trade is dependent on the type of goods traded. This highlights an urgency to understand the trade of waste and its effects.

In 2020, 32.7 million tons of waste were exported out of the European Union and 16 million tons of waste were imported into the European Union (Eurostat, 2021). This means there is a net export of 16.7 million tons of waste from the EU in 2020. In comparison, only 18.7 million tons of waste were exported out of the EU and 17.7 million tons of waste were imported into the EU (Eurostat, 2021). This means there is a net export of 1 million ton of waste in 2004. This further implies that between 2004 and 2020, the export of waste has increased by 75% and the import of waste has increased by 6%, furthermore, the net export of waste has increased by 157% (Eurostat, 2021).

According to the 1013/2006 EC directive on the shipments of waste, EU countries are banned from exporting common waste out of the EU for disposal (European Parliament, 2006). This includes exporting harmful waste to developing nations for waste disposal or recovery. The directive has also stated that hazardous could only be shipped to OECD countries for recovery (European Parliament, 2006).

The results of the Basel convention were implemented into EU law (Geeraerts, et al., 2015), and one of the most notifiable rule was that EU countries cannot export electronic waste outside the Union. Despite being implemented into EU law, illegal shipments of electronic waste still continues. Geeraerts et al. has found that around 8 million tons of electronic waste are illegally exported to China annually. The authors argued that the main reason for the illegal export is due to high profit margins, but the different levels of law enforcements by each member state also plays a crucial role in the illegal activity.

Eurostat has reported that the largest importer of EU waste was Turkey in 2020. Turkey imported 13.7 million tons of waste in 2020, which accounts for more than half of the waste exported from EU (Eurostat, 2021). The second largest importer of EU waste is India, followed by UK (Eurostat, 2021). The most common type of waste exported are iron and steel, which accounts for 17.4 million tons of waste (Eurostat, 2021). The second most common type of waste exported is paper and cardboard, with 6.1 million tons in 2020 (Eurostat, 2021).

3.2 Aim of this Chapter

The aim of this chapter is to lightly explore the social structures of trade on waste paper and cardboard with European countries in 2020 using network analysis. By examining trade as a relational topic, a better understanding on the intimacies of waste paper and cardboard trade could potentially be achieved.

3.3 Data and Methods

The methodology of this paper is sparsely based on the paper by Wang et al. (2020) and Beaton et al. (2017). In the paper by Wang et al., the authors examined the global trade network of plastic waste using network analysis. The authors found that after China's import ban on waste, plastic waste has been redirected to poorer countries in South East Asia. Wang et al. highlighted that developing countries have the leverage in banning plastic waste imports, since developed countries have no intention in shipping and shifting plastic waste to poorer countries. This finding corroborates with previous findings by Singh and Mukherjee (2019).

In the paper by Beaton et al. (2017), the authors examined the trade in Latin American and Caribbean countries using network analysis. The authors have explored regional and global trade networks with Caribbean and Latin American countries using centrality measures. The authors have found that the overall structure between the countries are weak, but well integrated (Beaton, et al., 2017). When compared to countries outside of the region, the authors have found that the Latin American and Caribbean networks are weakly integrated.

In this chapter, three networks on the trade of paper and cardboard waste[19] will be analyzed through the use of network analysis. We will be analyzing the full trade network, the import network and the export network. The full trade network includes both import and export of paper and cardboard waste. The import network includes paper and cardboard waste imported by European countries. The export network includes paper and cardboard waste exported by European countries.

All data are extracted from the Eurostat Comext / International Trade in Goods (ITGS) database. All networks examined are from the year of 2020. Due to the remarkably skewed nature of the quantity traded between countries, only the top 50% of the network are examined. This is to ensure a full examination on the more important trade links. All analysis are completed in R and the codes are given in the appendix. The trade networks are constructed as follows:

- $N = \{N_1, N_2,\ldots,N_i\}$, representing the vertices of the network, of which are the countries.
- $L = \{L_1,L_2,\ldots,L_j\}$, representing the edges of the network, of which represent the direction of trade between countries.
- $Q = \{Q_1,Q_2,\ldots,Q_k\}$, representing the weights of the edges, of which represent the quantity traded in hundred kilograms.

This means that each network, denoted as P, is a list of N, L, and Q, thus giving the expression of $P = \{N, L, Q\}$. As all three networks are directed networks, it is important to understand the graphical representation. In a directed network, an arrow between two nodes means that there is a link between the two nodes. The node that the arrow is pointing towards, e.g. 'A' → 'B', means that 'A' exported paper and cardboard waste to 'B'. Conversely if the arrow is point the other direction, e.g. 'A' ← 'B' , it means that 'A' imported waste from 'B'. Likewise, you can also interpret 'A' ← 'B' as 'B' exported waste to 'A'. The list of countries examined are European countries and its partners. All networks will be interpreted from the point of view of European countries.

In the next section, several results of the network will be presented. The section will start with descriptive statistics on the amount of paper and cardboard waste traded in 2020, followed by a presentation of the network graphs and statistics, with centrality measures and then ends with structural detection.

3.4 Results of the Waste Network

3.4.1 Descriptive Statistics

This subsection explores the basic nature on the amount of paper and cardboard waste imported and exported.

[19] This is coded as 4707 on the Eurostat Comext/International Trade in Goods database.

Table 15: Descriptive Statistics of Paper and Cardboard Waste Traded in 2020 by country and partner

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Imported Waste (hundred kilograms)	0	42	2933	221156	49627	12551072
Exported Waste (hundred kilograms)	0	29	3553	1877604	51911	11555731

Source: Eurostat
Note: these are from the full data set.

Table 15 shows the descriptive statistics of paper and cardboard waste traded from the European Union in 2020 by country and partner. As one can observe, both variables are rather skewed, especially where the mean and the median are largely deviated of each other.

In 2020, the highest amount of paper and cardboard waste imported was 12551072 hundred kilograms (roughly 1.26 million tons) from the Netherlands to Germany. The biggest non-European[20] partner who exported paper and cardboard waste to EU countries was the United States, with 978736 hundred kilograms.

The highest amount of waste exported was 11555731 hundred kilograms (around 1.16 million tons) from France to Spain[21]. The biggest non-European partner who imported paper and cardboard from EU countries was Indonesia, with 5784021 hundred kilograms.

[20] In this chapter, there is a fine distinction between European and EU. When the word 'European' is used, it signifies the region of Europe, and when the word 'EU' is used, it signifies countries in the European Union.

[21] Understandably, one might gasp at this trade asymmetry. However, this is a common problem in dealing with trade data. For more discussion on this topic, please see the Eurostat help page (Eurostat, 2021).

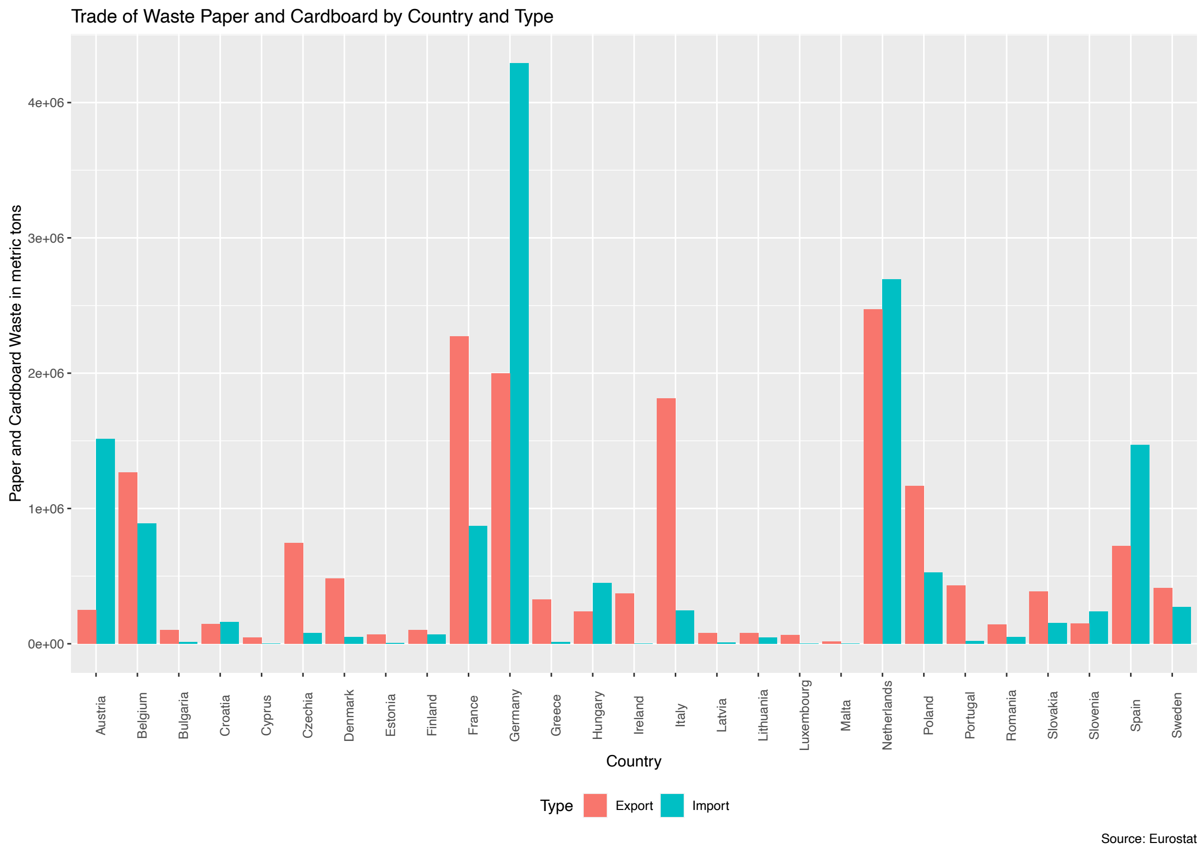
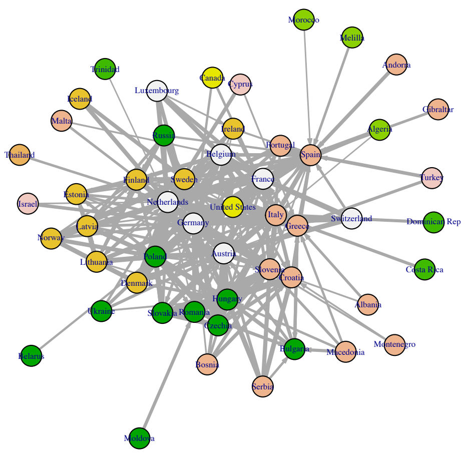


Figure 22: Bar graph of Waste Paper and Cardboard by Country and Type of Trade (2020)

Figure 22 shows the total amount of paper and cardboard waste imported or exported by each EU country. Germany imported the most paper and cardboard waste, followed by Netherlands, and then Austria. The Netherlands exported the most waste paper and cardboard, followed by France, and then Germany.

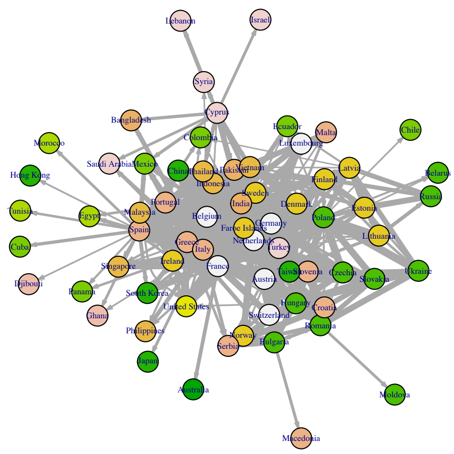
3.4.2 Network Graphs and Statistics

2020 EU Import Network of Waste Paper and Cardboard



Source: Eurostat

2020 EU Export Network of Waste Paper and Cardboard



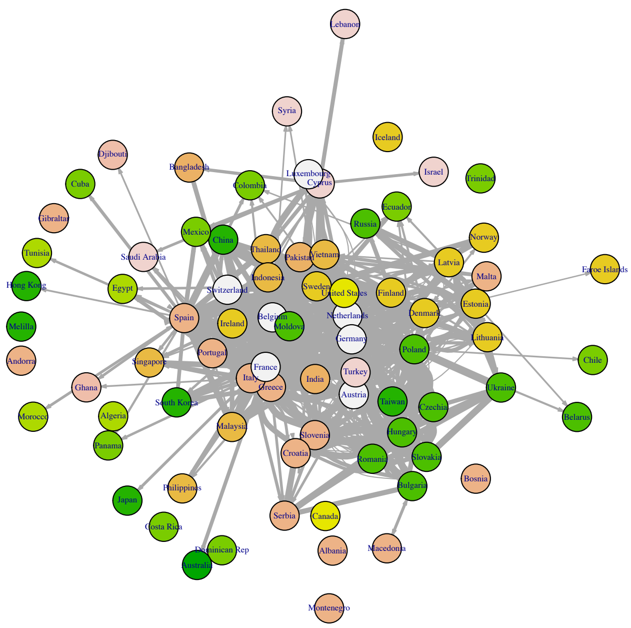
Source: Eurostat

Figure 23[22]: Graphs of the Import and Export Network on Waste Paper and Cardboard

Figure 23 graphs the import and export networks on the trade of waste paper and cardboard. The nodes are color coded according to the UN sub-regional classifications (UN Statistics Division, 2021). The thickness of the edges represent the quantity of waste traded between the countries. As we can see from both graphs, the trade between EU countries are rather complex. It is important to note that EU countries trade with countries that are further away, such as Chile, besides countries that are geographically close to Europe, e.g. Turkey.

[22] The nodes are assigned colors for an easier interpretation of the graph. Unfortunately the color codes are not consistent throughout this chapter. This is due to each graph are generated independently and color matching is automatically assigned each time.

2020 EU Full Trade Network of Waste Paper and Cardboard



Source: Eurostat

Figure 24: Graph of the Trade Network on Waste Paper and Cardboard

Figure 24 depicts the full trade network of waste paper and cardboard. From the full trade network, the relation between countries are even more entangled. One can see that there are some clustering between certain groups of countries, however, this is only indicative and not absolute. It is important to note that not all edges are visible in figure 24.

Table 16: Network Statistics of All Three Networks

Network	Number of Edges	Number of Nodes	Density	Average Path Length	Transitivity	Diameter
Full	756	80	0.120	2.185	0.421	4
Import	320	52	0.121	2.045	0.469	4
Export	436	68	0.096	2.005	0.411	4

In the full network, there are 756 edges and 80 vertices/nodes. The density of a network signifies the percentage of present edges compared to all possible edges. In the full network, only 12% of all possible edges are present. The average path length tells us the average number of steps from one vertex to another (Newman, 2018). This means that the average number of steps from one country to another is 2.185 steps. Transitivity calculates the likelihood of two connected vertices joining with a third vertex to create a triad (Newman, 2018). In the full network, there is a 42.1% chance that two countries with an existing relation will connect with a third country. The diameter shows the longest path in the network. In the full network, the longest path takes four steps. With the low average path length and a moderate transitivity, the full network could potentially be a small-world network.

The import network consists of 320 edges and 52 nodes. Only 12.1% of all possible edges are present in the import network. The average number of steps from one node to another is 2.045 steps. There is a 46.9% chance that two existing vertices with a relation will form a relation with a third vertex and the longest path length in the import network is 4 steps. With the moderate transitivity and low average path length, the import network could potentially be a small-world network.

The export network consists of 68 nodes and 436 edges. Only 9.6% of all possible edges are present in the export network. The average number of steps from one node to another is 2.005 steps. The longest path length in the export network is 4 steps and there is a 41.1% chance that two existing nodes with a relation will form a relation with a third node. With a low average path length and a moderate transitivity, the export could potentially be a small-world network.

3.4.3 Centrality Measures

Table 17: Highest Centrality Measures of the Full, Import, and Export Networks

Network	Degree Centrality	Eigenvector Centrality	Betweenness Centrality
Full	Netherlands 103	Germany 1	Germany 2016
Import	Netherlands 46	Germany 1	Netherlands 700
Export	Netherlands 57	Netherlands 1	Germany 1231

Centrality measures can tell us certain characteristics of the graph. Degree centrality is simply a measure of how many edges each node has (Newman, 2018). Eigenvector centrality measures the uniqueness of each node by comparing the edges it has with other nodes in proportion to the quantity traded (Newman, 2018). Betweenness centrality measures how a node is a link for other nodes.

In the full network, the Netherlands has the highest degree centrality with 103 edges. This means that in 2020, the Netherlands traded uniquely 103 times in both import and export. Germany has the highest eigenvector centrality with 1, which means that Germany trades the most waste paper and cardboard with other important countries. Germany has the highest betweenness centrality, with a score of 2016. This means that Germany is the most important link in the network to trade with other countries. All these measures signifies that although the Netherlands has the most links, but Germany trades the most with other important countries and is the most important broker (Burt, 2004) between countries in terms of the trade in paper and cardboard waste.

In the import network, the Netherlands has the highest degree centrality with 46 edges. This indicates that the Netherlands has uniquely imported from 46 countries. Germany has the highest eigenvector centrality of 1, meaning that Germany has imported paper and cardboard waste from other important countries. The country with the highest betweenness centrality in the import network is the Netherlands. This means that in terms of imports, the Netherlands is a link for importing with other countries. Deducing from the three centrality measures, the Netherlands is an important player in terms of waste paper and cardboard imports. Not only does the Netherlands have the most links with other countries, but the country is also a broker between countries.

In the export network, Germany has the highest betweenness centrality. This means that Germany is the most important broker between country in terms of the export in paper and cardboard. On the other hand, the Netherlands has the most ties (57 countries) and the highest eigenvector centrality. This means that the Netherlands exports to other important countries.

3.4.4 Structural Detection

In this subsection, we will be looking at the overall structure of trade of all three networks. The overall structure will be seen through the lens of Louvain community detection. For further analysis using hierarchical cluster and structural equivalence please see Appendix A.

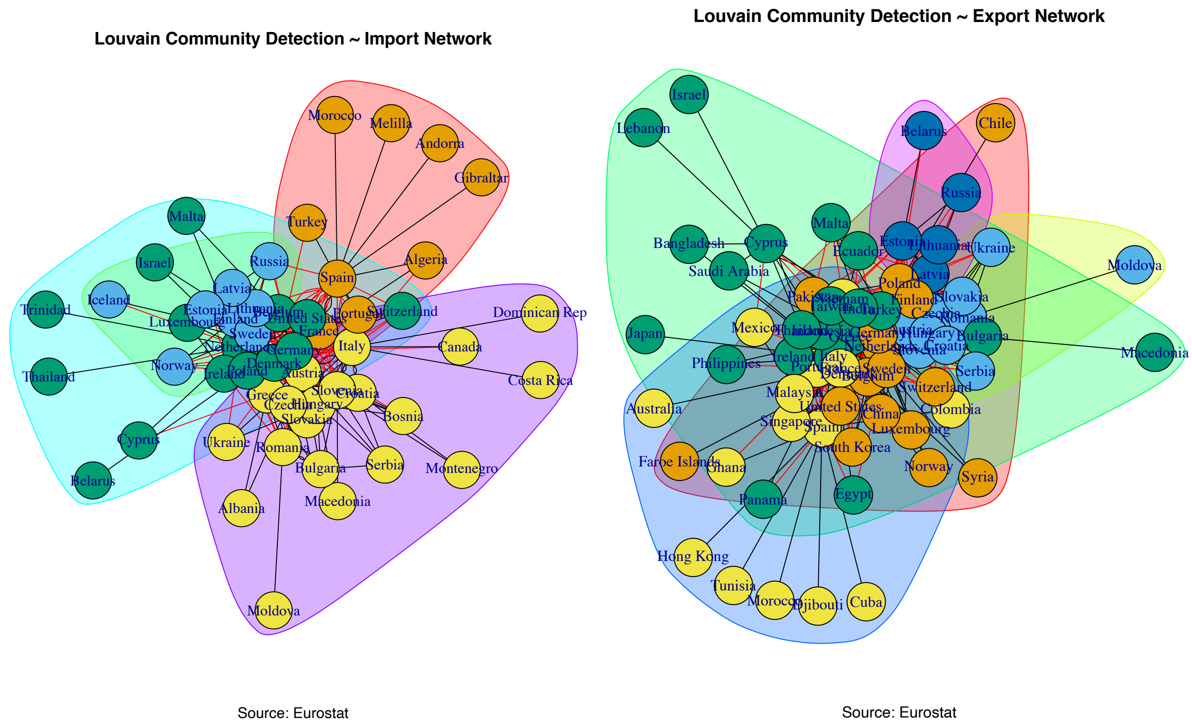


Figure 25: Louvain Community Detection of Import and Export Networks

Figure 25 shows the results of both import and export networks after using the Louvain community detection. For the import network, the Louvain algorithm detected four main groups. The groups are listed in table 18.

Table 18: Louvain Community Detection Results for the Import Network

Group 1	Group 2	Group 3	Group 4
France, Algeria, Morocco, Portugal, Spain, Melilla, Gibraltar, Turkey, and Andorra	Finland, Sweden, Lithuania, Latvia, Estonia, Norway, Russia, and Iceland	Netherlands, Ireland, Trinidad, Belgium, Israel, Poland, Luxembourg, United States, Denmark, Cyprus, Malta, Belarus, Thailand, Germany, and Switzerland	Greece, Italy, Romania, Austria, Bosnia, Montenegro, Albania, Ukraine, Slovakia, Croatia, Hungary, Canada, Macedonia, Serbia, Bulgaria, Slovenia, Dominican Republic, Costa Rica, Moldova, and Czech Republic

Groups 1, 2, and 4 seems to be geographically dominated. The countries listed in group 1 all seem to be along the Mediterranean. Group 2 countries are all in the northern Europe / Baltic states with the inclusion of Russia. Group 4 countries are all close to each other in central and eastern Europe, with the exception of Canada, Costa Rica, and Dominican Republic. Group 3 is a mix of Benelux countries and its neighbors, as well as all other countries not included in the previous three groups.

Table 19: Louvain Community Detection Results for the Import Network

Group 1	Group 2	Group 3	Group 4	Group 5
Denmark, Netherlands, Belgium, Sweden, Poland, Finland, Germany, Luxembourg, Faroe Islands, Pakistan, Syria, United States, Chile, China, Norway, Switzerland, and South Korea	Czechia, Slovenia, Austria, Hungary, Romania, Croatia, Slovakia, Ukraine, Serbia, and Moldova	Ireland, Greece, Cyprus, Italy, Bulgaria, Malta, Turkey, Ecuador, Saudi Arabia, Indonesia, Taiwan, India, Thailand, Egypt, Philippines, Panama, Israel, Japan, Macedonia, Bangladesh, and Lebanon	Portugal, Spain, France, Colombia, Vietnam, Singapore, Djibouti, Malaysia, Ghana, Hong Kong, Tunisia, Morocco, Mexico, Cuba, and Australia	Latvia, Lithuania, Estonia, Belarus, and Russia

For the export network, the algorithm detected five main groups. Group 5 and group 2 are regionally dominated, with group 5 consisting of countries along the Baltic sea and group 2 consisting of countries in central and eastern Europe. Groups 1, 3, and 4 offer a variety of countries together. All three groups have a mix of countries from different regions and could not be generalized, but certain countries from the same group could possibly offer a clue about its structure. Group 1 consists of Benelux countries and its neighbors, and Nordic countries. Group 3 mainly consists of Asian countries and Mediterranean countries.

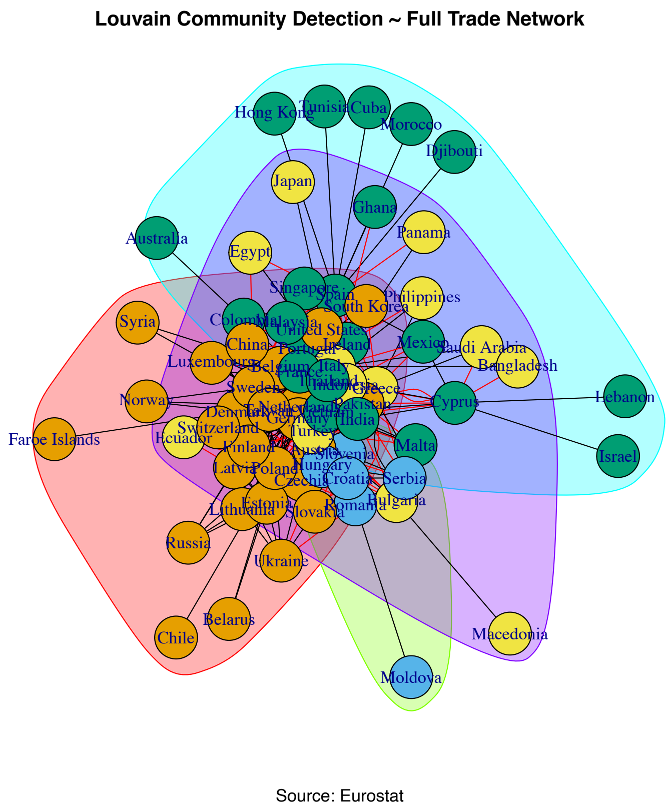


Figure 26: Louvain Community Detection of the Full Network

Figure 26 shows the results of the Louvain algorithm applied to the full trade network. The algorithm detected four groups of countries, and are listed in the table below.

Table 20: Louvain Community Detection Results for the Full Trade Network

Group 1	Group 2	Group 3	Group 4
Czechia, Denmark, Netherlands, Austria, Latvia, Lithuania, Belgium, Estonia, Sweden, Poland, Finland, Germany, Slovakia, Luxembourg, Faroe Islands, Pakistan, Syria, United States, Chile, Belarus, Taiwan, China, Norway, Switzerland, Ukraine, South Korea, and Russia	Slovenia, Hungary, Romania, Croatia, Serbia, and Moldova	Portugal, Ireland, Spain Cyprus, France, Malta, Colombia, Vietnam, Singapore, Djibouti, Malaysia, Ghana, Hong Kong, India, Thailand, Tunisia, Morocco, Israel, Mexico, Cuba, Australia, and Lebanon	Greece, Italy, Bulgaria, Turkey, Ecuador, Saudi Arabia, Indonesia, Egypt, Philippines, Panama, Japan, Macedonia, and Bangladesh

By looking at the countries in each group, the results are even more varied than the results from the import or export network. It is clear that group 2 consists of countries from eastern Europe, but group 1, 3, and 4 are an assortment of countries from all different regions.

3.5 Chapter Discussion and Conclusion

This chapter focused on exploring the trade network of waste paper and cardboard with European countries. The chapter started with a descriptive analysis on the quantity traded, followed by a network analysis of the trade network. The network analysis focused on network statistics, centrality measures, and social structure of the network. Each section of the network analysis examined the import network, the export network, and the full trade network (with both imports and exports combined).

From figure 22, one could observe that Germany is the largest importer of paper and cardboard waste and the Netherlands is the largest exporter of paper and cardboard waste in 2020. According to the German Environment Agency, the main reason for the high amount of waste paper and cardboard import is to recycle them and turn into recycled paper and cardboard products (Wielenga & Junker, 2004). The main reason for the high exports of waste paper and cardboard from the Netherlands is because the Netherlands is a hub for other European countries to export their waste (Spapens, et al., 2019). In particular, waste from other EU countries will first be sorted in the Netherlands and then recyclable materials will get exported to other countries (Mehlbaum & Spapens, 2017).

All three networks examined in this chapter display characteristics of a small-world network. This is due to the low average path length and the moderate transitivity. This means that in all three networks, to transport waste paper and cardboard from one country to another country takes on average 2 steps. The transitivity of all three networks are moderate, neither high or low. However, further analysis is needed to fully determine which kind of model each network is. The randomness and the hubs that links to other isolated countries are characteristics of a small-world network as well.

The results of the centrality measures are not surprising. As discussed above, the Netherlands acts like a hub for other European countries to further transport waste paper and cardboard. It is worth noting that Germany too, is an important country as indicated by the centrality measures. The high eigenvector and betweenness centrality means that Germany is a broker between countries in both directions of waste paper and cardboard trade Germany trades with other import countries as well.

The results of the Louvain community detection algorithm indicates that the trade of waste paper and cardboard is partially influenced by geographical location[23]. As we have seen, the location effect is the most prominent in the import network. For the export and the full trade network, the results of the algorithm is inconclusive, even though the location effect is still visible. In the full network, we can see that the grouping of countries are largely influenced by the export network. This is unsurprising as the volume of exports in waste paper and cardboard is far higher than the volume of imports in waste paper and cardboard.

From looking at the graphs of the export network (figure 23), it seems as if India is in the heart of waste paper and cardboard trade. This is particularly true, considering the fact that India is the biggest importer of European paper and cardboard waste, with around 1.6 million tons of waste paper and cardboard imported in 2020. Indonesia, being the second largest non-European importer of European waste paper and cardboard, imported 1.2 million tons of European waste paper and cardboard. This finding does not only corroborate with the previous findings of Singh Mukherjee (2019) but also contribute towards increasing evidence in waste dumping (Spapens, et al., 2019). In fact, Eurostat has reported since China's ban on waste imports, other less well-off countries have increased the import of European waste paper and

[23] In trade theory, this is observed when using the gravity model (Brun, et al., 2005).

cardboard (Eurostat, 2020). However, this finding should be solidified with further empirical analysis.

Limitations exist in this chapter. Despite this chapter being shorter than the other two chapters, this chapter provided a primer to analyze the trade of waste paper and cardboard using network analysis. This chapter has also provided a basic framework for furthering examinations on the topic of waste trade using network analysis. Hopefully with a more thorough examination using network analysis, some of the more pressing issues could be addressed, such as pollution haven and race to the bottom.

Other project ideas include looking at the trade of waste paper and cardboard through time, thus creating a dynamic network and thus one can observe the full effect of China's ban on importing waste. Another idea is to look at the trade of waste paper and cardboard globally, and by increasing the number of edges and nodes the analysis creates a fuller picture of the trade structure.

This chapter has also made me question myself on the economics of waste trade in general. Spapens et al. (2019) has mentioned that as long as the economic incentive for exporting waste outside of the Union is bigger than actual recycling within the EU, waste exports will continue. As Barnes (2019) and Cotta (2020) have summarized in their papers, waste export does not only shift environmental problems elsewhere, but it also creates an "artificial cleaner environment" (Barnes, 2019). However, the ethical judgement of waste import or export is out of scope for this chapter.

All findings in chapter three are particularly relevant towards a better waste management in the trade of paper and cardboard waste in the European Union. As a starter for waste trade policy, determining non-economic factors on waste export outside of the European Union would be beneficial.

This chapter looked at the trade of waste paper and cardboard from the viewpoint of European countries using network analysis. Early evidence suggest that the import of waste paper and cardboard is factored by geographical locations and unsurprisingly Germany and the Netherlands are influential when it comes to the trade of waste paper and cardboard.

General Conclusion

The topic of this thesis is to provide an outlook on waste in general in European countries. This thesis is divided into three chapters. Chapter one mainly examines the relationship between final consumption expenditure of households in current prices PPS per capita and municipal waste in kilograms per capita in European countries. The main theme of chapter two is to investigate the relationship between gross domestic product in current prices PPS per capita and packaging waste in kilograms per capita in European countries. The third chapter strives to explore the trade of paper and cardboard waste of European countries by using network analysis.

Chapter one found several different relationships between municipal waste indicators and final consumption expenditure of households. The relationship found between final consumption expenditure of households and total municipal waste is a positive quadratic relationship. The relationship found here is particularly alarming. Compared to the previous study by Mazzanti and Zoboli (2009), this relationship found meant that the total municipal waste is growing at a faster rate than previously thought.

The relationship found between landfilled municipal waste and final consumption expenditure of households are either negative quadratic, which confirms the Environmental Kuznets Curve, or negative cubic. It should be noted that the relationship found between landfilled municipal waste and final consumption expenditure of households is due to policy Mazzanti and Zoboli (2009). This means that the landfill directive set out by the European Commission effectively reduces landfilled municipal waste. The negative cubic relationship found is simply an indication that the amount of municipal waste landfilled is decreasing faster than before. Finally, the relationship found between final consumption expenditure of households and recycled materials of municipal waste is positive linear. This means that the amount of municipal waste recycled is increasing in European countries, with no clear signs of decreasing.

Various relationships between packaging waste and gross domestic product have been found in chapter two. Between total packaging waste generated and gross domestic product, a positive linear relationship has been found. Between gross domestic product and paper and cardboard packaging waste, a positive linear relationship has been found. Lastly, the same positive linear relationship has also been found between plastic packaging waste and GDP.

The relationships found in chapter two are hardly surprising. First, the relationship found between total packaging waste generated and gross domestic product corroborates with the previous study by Mazzanti and Zoboli (2005). Secondly, all three packaging waste indicators reveal to have a linear relationship, which indicate that the trend for packaging waste indicators will continue to increase without decreasing at any point. The relationships are unsurprising because the EC directive on packaging waste (Bourguignon, 2018), focuses on recovery and not a reduction of packaging waste. This sentiment echoes the same view as Mazzanti and Zoboli (2005).

Chapter three lightly explored the trade of paper and cardboard waste using network analysis. From the results of network statistics, one could observe that the networks analyzed display the characteristics of a small-world network. This means that the trade of paper and cardboard is relatively fast, and cliques are present in the networks. Using centrality measures, it has been revealed that the Netherlands and Germany are the most important actors in the trade of paper and cardboard waste. This means that in both directions of trade, a country should go to either country for access to other countries. In particular, if one would like to trade waste paper and cardboard in general with other countries, the Netherlands is the best country to go to. If one would like to trade with other influential countries, Germany is the best country to contact. By using the Louvain algorithm, it has been revealed that geographic location is a factor in the trade of paper and cardboard waste, which is known in trade theory as the gravity model.

Limitations certainly exist in this thesis. Both chapters one and two did not examine all possible panel regression effects such as the mixed effects or two-way effects. For further consolidation of the relationships found in chapters one and two, all other possible effects should be examined in the future. Chapter three provided a rather light analysis, but highlighted the complexities and intricacies of waste trade. For further analysis, a more thorough network analysis should be performed on the trade of paper and cardboard waste, and more attributes should be examined in order to determine which characteristics influence the trade of paper and cardboard waste.

Looking forward, there are still puzzles missing in the understanding of waste and waste trade in Europe. Further studies on factors influencing recycling or recovery rates should be examined. As with the trade of waste, numerous studies on the plastic waste trade already exist. Further studies on the other types of waste trade should further be explored to achieve a systematic understanding on the trade of waste.

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Appendix A: Further Analysis on the Trade Networks

First we will be looking at the results of the hierarchical cluster, through the use of dendrograms.

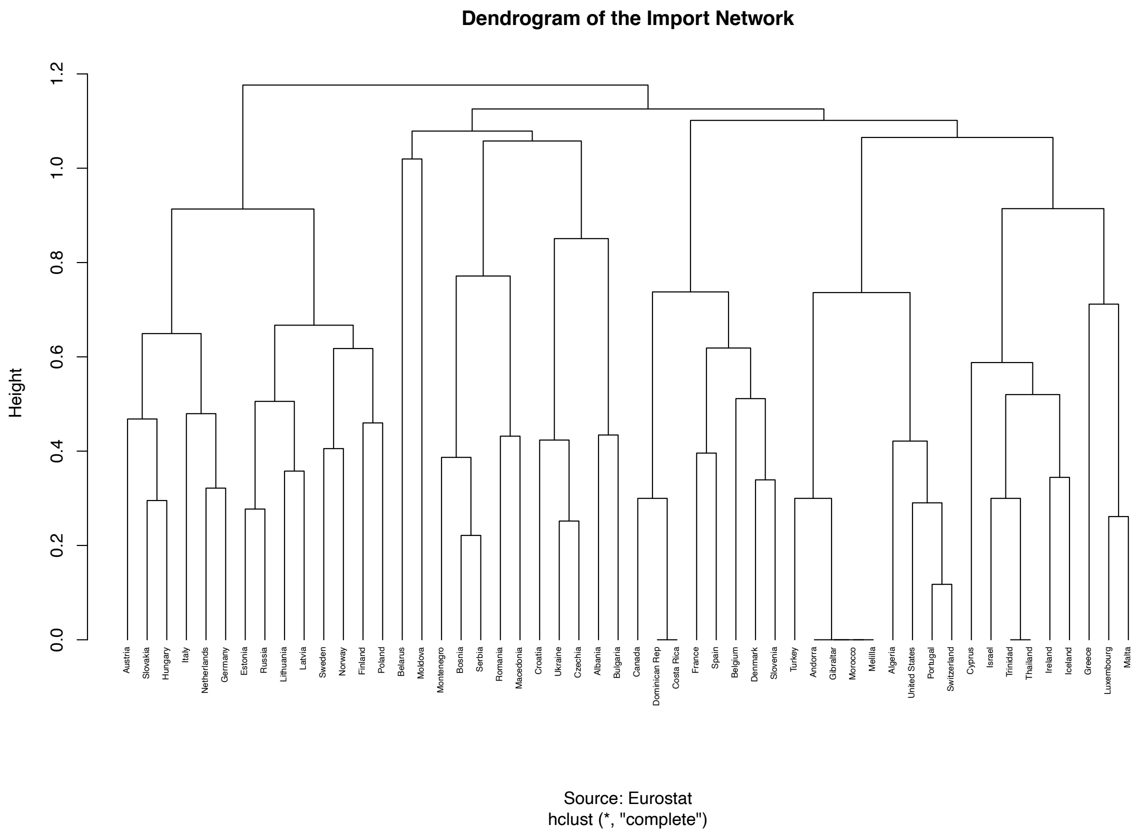

Figure 27: Dendrogram of the Import Network

From figure 27, we can see the various groupings of the import network through the use of hierarchical cluster. If we cut the graph at the height of 1.1, we have four groups of countries. The first group of countries goes from Austria to Poland. The second group of countries goes from Belarus to Bulgaria. The third group of countries goes from Canada to Slovenia. The fourth group of countries goes from Turkey to Malta. The geographical effect is still somehow observable in group one, e.g. Norway and Sweden are grouped close together, but the geographical effect is not as pronounced in the successive groups. It is interesting to note that Germany and the Netherlands are grouped together.

It is interesting to note that group three and four mainly consist of import partners for the EU, meaning that these countries supply the paper and cardboard waste for the EU.

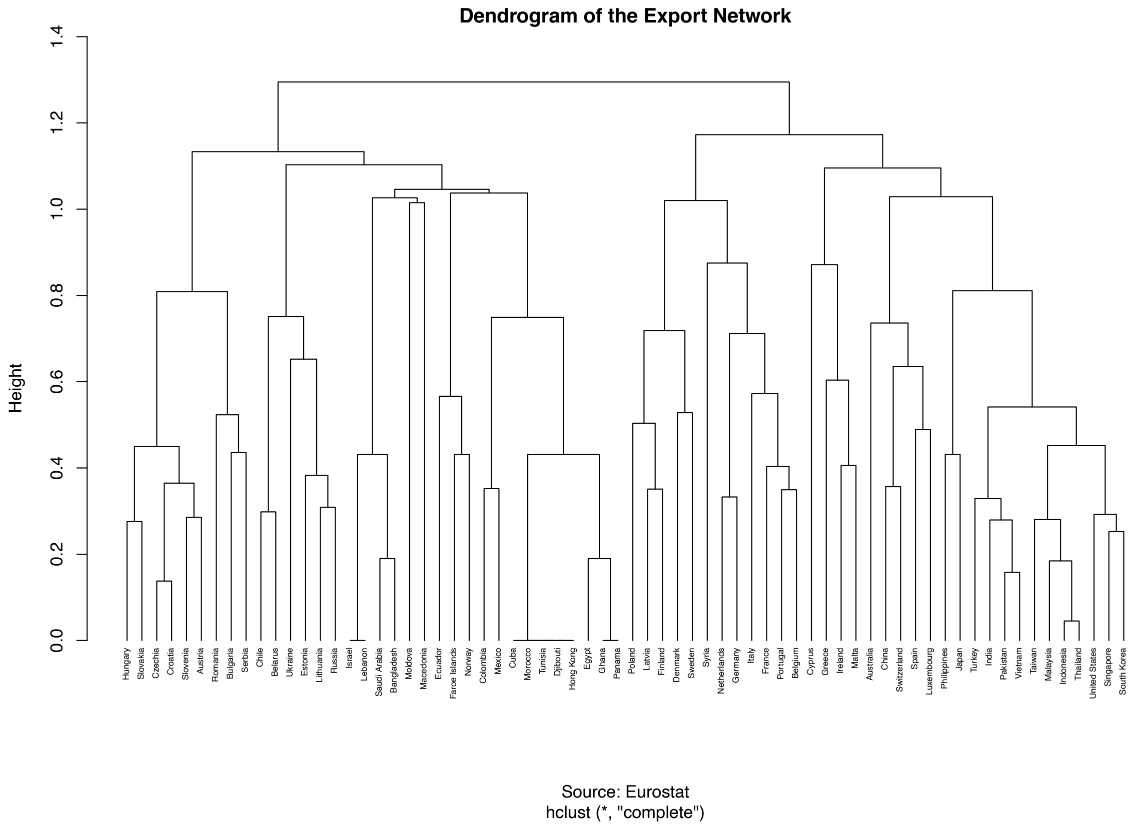

Figure 28: Dendrogram of the Export Network

If we cut the graph at the height of 1.2 in figure 28, two distinctive groups are observed. The first group goes from Hungary until Panama, and the second group goes from Poland to South Korea. The geographical effect is still there, but only at the lower levels of clustering. It is interesting to note that Germany and the Netherlands are still grouped together.

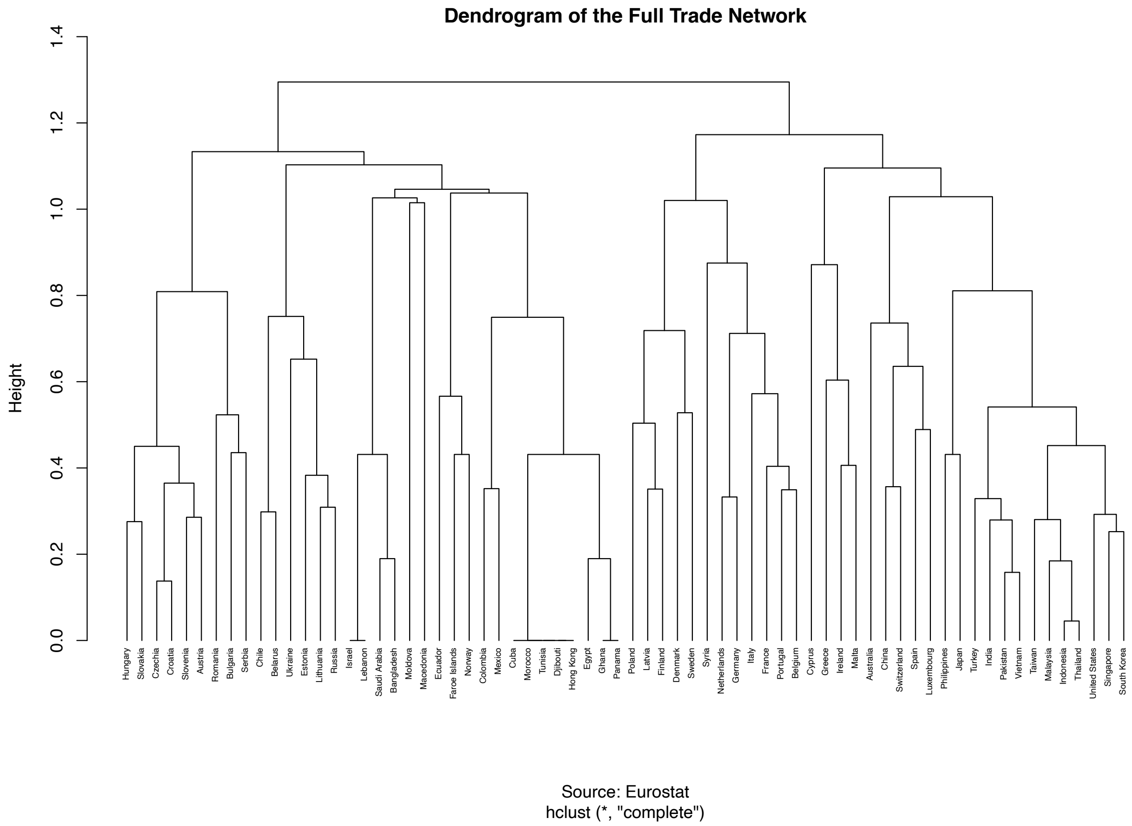

Figure 29: Dendrogram of the Full Trade Network

Figure 29 shows the clustering result of the full trade network of paper and cardboard waste. Compared to the clustering results of the export network, the results of the full network remains largely unchanged. This is unsurprising as the clustering algorithm takes into account of the quantity traded, and the quantity exported is much larger than the quantity imported thus resulting in two similar graphs.

Appendix B: R Codes Used in this Thesis

```
# Thesis Chapter 1
# Municipal Waste

require(readxl)
require(tidyverse)
require(ggpubr)
require(viridis)
require(plm)
require(lmtest)
require(tseries)

#### International Comparison ####

# Total Municipal Waste
total_desc <- read_excel("Desktop/Chapter 1/descriptive/total desc.xlsx")
totall = total_desc %>% rename(Region = country) %>% pivot_longer(-c(Region), names_to
= "Year", values_to = "total")

ggplot(data = totall, aes(x=Year,y=total,group=Region)) +
  geom_point(aes(color=Region,shape=Region),size=4) +
  labs(x="Year",y="Total Municipal Waste in kg per capita", title = "Total Municipal Waste
Generated over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Landfilled Municipal Waste
landfill_desc <- read_excel("Desktop/Chapter 1/descriptive/landfill desc.xlsx")
landfilledl = landfill_desc %>% rename(Region = country) %>% pivot_longer(-c(Region),
names_to = "Year", values_to = "landfill")

ggplot(data = landfilledl, aes(x=Year,y=landfill,group=Region)) +
  geom_point(aes(color=Region,shape=Region),size=4) +
  labs(x="Year",y="Landfilled Municipal Waste in kg per capita", title = "Landfilled
Municipal Waste  over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Incinerated Municipal Waste
incinerated_desc <- read_excel("Desktop/Chapter 1/descriptive/incinerated desc.xlsx")
incineratedl = incinerated_desc %>% rename(Region = country) %>% pivot_longer(-
c(Region), names_to = "Year", values_to = "incinerate")

ggplot(data = incineratedl, aes(x=Year,y=incinerate,group=Region)) +
  geom_point(aes(color=Region,shape=Region),size=4) +
  labs(x="Year",y="Incinerated Municipal Waste in kg per capita", title = "Incinerated
Municipal Waste for Disposal over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Recovered Municipal Waste
energy_recovery_desc <- read_excel("Desktop/Chapter 1/descriptive/energy recovery
desc.xlsx")
recoveredl = energy_recovery_desc %>% rename(Region = country) %>% pivot_longer(-
c(Region), names_to = "Year", values_to = "recover")
```

```
ggplot(data = recoveredl, aes(x=Year,y=recover,group=Region)) +
  geom_point(aes(color=Region,shape=Region),size=4) +
  labs(x="Year",y="Recovered Municipal Waste in kg per capita", title = "Recovered
Municipal Waste for Energy over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Recycled Municipal Waste
recyc_desc <- read_excel("Desktop/Chapter 1/descriptive/recyc desc.xlsx")
recyclel = recyc_desc %>% rename(Region = country) %>% pivot_longer(-c(Region),
names_to = "Year", values_to = "recycle")

ggplot(data = recyclel, aes(x=Year,y=recycle,group=Region)) +
  geom_point(aes(color=Region,shape=Region),size=4) +
  labs(x="Year",y="Recycled Municipal Waste in kg per capita", title = "Recycled Municipal
Waste of Materials over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

rm(list = ls())
#### Preparing Data for Panel Regression ####

income <- read_excel("Desktop/Chapter 1/FCE Households.xlsx")
incomelong = income %>% pivot_longer(-c(country), names_to = "year", values_to = "fceo")

total <- read_excel("Desktop/Chapter 1/total.xlsx")
totallong = total %>% pivot_longer(-c(country), names_to = "year", values_to = "totalo")
totalw = left_join(totallong, incomelong, by = c("country","year"))
saveRDS(totalw, file = "totalw.rds")

landfilled <- read_excel("Desktop/Chapter 1/landfilled.xlsx")
landfilledlong = landfilled %>% pivot_longer(-c(country), names_to = "year", values_to =
"lando")
landw = left_join(landfilledlong, incomelong, by = c("country","year"))
saveRDS(landw, file = "landw.rds")

recycling_of_materials <- read_excel("Desktop/Chapter 1/recycling of materials.xlsx")
recyclong = recycling_of_materials %>% pivot_longer(-c(country), names_to = "year",
values_to = "recyco")
recycw = left_join(recyclong, incomelong, by = c("country","year"))
saveRDS(recycw, file = "recycw.rds")

#### Panel Descriptives ####

# TOTAL
totalw <- readRDS("~/Desktop/Chapter 1/totalw.rds")
summary(totalw)

panel1 = totalw %>% mutate(fce = log(fceo),fce2 =
log(fceo)*log(fceo),fce3=log(fceo)*log(fceo)*log(fceo),total=log(totalo),.keep="unused")

ggplot(data = panel1, aes(x=fce,y=total)) +
  geom_point(aes(color=country)) +
```

```
  labs(color="Country", x="ln(Final Consumption Expenditure of Households) in current prices
PPS per capita",y="ln(Total Municipal Waste) in kg per capita", title = "Total Municipal
Waste vs Income", caption="Source: Eurostat") + theme(legend.position = "bottom") +
scale_color_viridis(discrete=TRUE)

ggplot(data = panel1, aes(x=fce,y=total)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(Final Consumption Expenditure of Households) in current prices
PPS per capita",y="ln(Total Municipal Waste) in kg per capita", title = "Total Municipal
Waste vs Income by Country", caption="Source: Eurostat") + theme(legend.position =
"bottom") + scale_color_viridis(discrete=TRUE) +
  facet_wrap(~country,scales = "free") +
  theme(legend.position = "none")

# LANDFILL

landw <- readRDS("~/Desktop/Chapter 1/landw.rds")
summary(landw)

panel2 = landw %>% mutate(fce = log(fceo),fce2 =
log(fceo)*log(fceo),fce3=log(fceo)*log(fceo)*log(fceo),land=log(lando),.keep="unused")
%>% mutate_if(is.numeric, ~ifelse(abs(.) == Inf,0,.))

ggplot(data = panel2, aes(x=fce,y=land)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(Final Consumption Expenditure of Households) in current prices
PPS per capita",y="ln(Landfilled Municipal Waste) in kg per capita", title = "Landfilled
Municipal Waste vs Income", caption="Source: Eurostat") + theme(legend.position = "bottom")
+ scale_color_viridis(discrete=TRUE)

ggplot(data = panel2, aes(x=fce,y=land)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(Final Consumption Expenditure of Households) in current prices
PPS per capita",y="ln(Landfilled Municipal Waste) in kg per capita", title = "Landfilled
Municipal Waste vs Income by Country", caption="Source: Eurostat") + theme(legend.position
= "bottom") + scale_color_viridis(discrete=TRUE) +
  facet_wrap(~country,scales = "free") +
  theme(legend.position = "none")

# RECYCLING

recycw <- readRDS("~/Desktop/Chapter 1/recycw.rds")
summary(recycw)

panel3 = recycw %>% mutate(fce = log(fceo),fce2 =
log(fceo)*log(fceo),fce3=log(fceo)*log(fceo)*log(fceo),recyc=log(recyco),.keep="unused")
%>% mutate_if(is.numeric, ~ifelse(abs(.) == Inf,0,.))

ggplot(data = panel3, aes(x=fce,y=recyc)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(Final Consumption Expenditure of Households) in current prices
PPS per capita",y="ln(Recycled Municipal Waste) in kg per capita", title = "Recycled
```

```
Materials of Municipal Waste vs Income", caption="Source: Eurostat") + theme(legend.position
= "bottom") + scale_color_viridis(discrete=TRUE)

ggplot(data = panel3, aes(x=fce,y=recyc)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(Final Consumption Expenditure of Households) in current prices
PPS per capita",y="ln(Recycled Municipal Waste) in kg per capita", title = "Recycled
Materials of Municipal Waste vs Income by Country", caption="Source: Eurostat") +
theme(legend.position = "bottom") + scale_color_viridis(discrete=TRUE) +
  facet_wrap(~country,scales = "free") +
  theme(legend.position = "none")

#### TOTAL Panel Regression PANEL 1 ####

plm::is.pbalanced(panel1$country,panel1$year) # check if it is a balanced panel

# fixed effects
fe1 = plm(total ~ fce, data = panel1,index=c("country","year"),model="within") # total
summary(fe1, vcovHC)

# fixed effects with squared term
fe2 = plm(total ~ fce + fce2, data = panel1,index=c("country","year"),model="within")
summary(fe2, vcovHC)

# fixed effects with cubic term
fe3 = plm(total ~ fce + fce2 + fce3, data =
panel1,index=c("country","year"),model="within")
summary(fe3, vcovHC)

# random effects
re1 = plm(total ~ fce, data = panel1,index=c("country","year"),model="random")
summary(re1, vcovHC)

#random effects with squared term
re2 = plm(total ~ fce + fce2, data = panel1,index=c("country","year"),model="random")
summary(re2, vcovHC)

#random effects with cubic term
re3 = plm(total ~ fce + fce2 + fce3, data =
panel1,index=c("country","year"),model="random")
summary(re3, vcovHC)

# fixed effects with time
fet1 = plm(total ~ fce + factor(year), data=panel1, model="within")
summary(fet1,vcovHC)

fet2 = plm(total ~ fce + fce2 + factor(year), data=panel1, model="within")
summary(fet2,vcovHC) # with squared term.

fet3 = plm(total ~ fce + fce2 + fce3 + factor(year), data=panel1, model="within")
summary(fet3,vcovHC) # with cubic term

# random effects with time
```

```
ret1 = plm(total ~ fce + factor(year), data=panel1,
model="random",index=c("country","year"))
summary(ret1,vcovHC)

ret2 = plm(total ~ fce + fce2 + factor(year), data=panel1,
model="random",index=c("country","year"))
summary(ret2,vcovHC) # with squared term

ret3 = plm(total ~ fce + fce2 + fce3 + factor(year), data=panel1,
model="random",index=c("country","year"))
summary(ret3,vcovHC) # with cubic term

# panel diagnostics

cor(panel1$fce,panel1$total, method="pearson") # The correlation between the two
variables is 0.5564985.

pt1 = plm(total ~ fce + fce2 + fce3 + factor(year) + factor(country), data=panel1,
model="pooling")
plmtest(pt1, type=c("bp")) # reject HO, and state that there is a panel effect, therefore
pooled OLS is not appropriate
pt2 = plm(total ~ fce + fce2 + factor(year) + factor(country), data=panel1,
model="pooling")
plmtest(pt2, type=c("bp")) # there is a panel effect
pt3 = plm(total ~ fce + factor(year) + factor(country), data=panel1, model="pooling")
plmtest(pt3, type=c("bp")) # there is a panel effect

pFtest(fet2,fe2) # reject HO, and state there is a time effect
pFtest(ret2,re2) # there is a time effect
plmtest(fet2, c("time"), type=("bp")) # there is a time effect
plmtest(ret2, c("time"), type=("bp")) # there is a time effect

adf.test(panel1$total, k=2)
# Because p-value < 0.05, therefore the series dos not have unit roots. This means that the
series is stationary
adf.test(panel1$fce, k=2) # stationary
adf.test(panel1$fce2, k=2) # stationary
adf.test(panel1$fce3, k=2) # stationary

# Model diagnostics
# All of these tests need to be performed individually for the models we would like to
compare

phtest(fet2,ret2) # fail to reject null (random) and state that the random effects is more
appropriate

pcdtest(fet2) # not cross-sectional dependent
pcdtest(ret2) # not cross-sectional dependent

pbgtest(fet2) # there is serial correlation
pbgtest(ret2) # there is serial correlation
```

```
bptest(total ~ fce + factor(year), data = panel1, studentize=F) # fail to reject HO, thus there's no heteroskedaticity
bptest(total ~ fce + fce2 + fce3 + factor(year), data = panel1, studentize=F) # reject HO, thus there is heteroskedaticity

#### LANDFILLED Panel Regression PANEL 2 ####

plm::is.pbalanced(panel2$country,panel2$year) # check if it is a balanced panel

# fixed effects
fe1 = plm(land ~ fce, data = panel2,index=c("country","year"),model="within") # land
summary(fe1, vcovHC)

# fixed effects with squared term
fe2 = plm(land ~ fce + fce2, data = panel2,index=c("country","year"),model="within")
summary(fe2, vcovHC)

# fixed effects with cubic term
fe3 = plm(land ~ fce + fce2 + fce3, data = panel2,index=c("country","year"),model="within")
summary(fe3, vcovHC)

# random effects
re1 = plm(land ~ fce, data = panel2,index=c("country","year"),model="random")
summary(re1, vcovHC)

#random effects with squared term
re2 = plm(land ~ fce + fce2, data = panel2,index=c("country","year"),model="random")
summary(re2, vcovHC)

#random effects with cubic term
re3 = plm(land ~ fce + fce2 + fce3, data = panel2,index=c("country","year"),model="random")
summary(re3, vcovHC)

# fixed effects with time
fet1 = plm(land ~ fce + factor(year), data=panel2, model="within")
summary(fet1,vcovHC)

fet2 = plm(land ~ fce + fce2 + factor(year), data=panel2, model="within")
summary(fet2,vcovHC) # with squared term.

fet3 = plm(land ~ fce + fce2 + fce3 + factor(year), data=panel2, model="within")
summary(fet3,vcovHC) # with cubic term

# random effects with time
ret1 = plm(land ~ fce + factor(year), data=panel2, model="random",index=c("country","year"))
summary(ret1,vcovHC)

ret2 = plm(land ~ fce + fce2 + factor(year), data=panel2, model="random",index=c("country","year"))
summary(ret2,vcovHC) # with squared term
```

```
ret3 = plm(land ~ fce + fce2 + fce3 + factor(year), data=panel2,
model="random",index=c("country","year"))
summary(ret3,vcovHC) # with cubic term

# panel diagnostics

cor(panel2$fce,panel2$land, method="pearson") # The correlation between the two
variables is 0.5564985.

pt1 = plm(land ~ fce + fce2 + fce3 + factor(year) + factor(country), data=panel2,
model="pooling")
plmtest(pt1, type=c("bp")) # reject HO, and state that there is a panel effect, therefore
pooled OLS is not appropriate
pt2 = plm(land ~ fce + fce2 + factor(year) + factor(country), data=panel2,
model="pooling")
plmtest(pt2, type=c("bp")) # there is a panel effect
pt3 = plm(land ~ fce + factor(year) + factor(country), data=panel2, model="pooling")
plmtest(pt3, type=c("bp")) # there is a panel effect

pFtest(fet2,fe2) # reject HO, and state there is a time effect
pFtest(ret2,re2) # there is a time effect
pFtest(fet3,fe3) # there is a time effect
pFtest(fet1,fe1) # there is a time effect
pFtest(ret3,re3) # there is a time effect
plmtest(fet2, c("time"), type=("bp")) # there is a time effect
plmtest(ret2, c("time"), type=("bp")) # there is a time effect
plmtest(fet3, c("time"), type=("bp")) # there is a time effect

adf.test(panel2$land, k=2)
# Because p-value < 0.05, therefore the series dos not have unit roots. This means that the
series is stationary
adf.test(panel2$fce, k=2) # stationary
adf.test(panel2$fce2, k=2) # stationary
adf.test(panel2$fce3, k=2) # stationary

# Model diagnostics
# All of these tests need to be performed individually for the models we would like to
compare

phtest(fet2,ret2) # fail to reject null (random) and state that the random effects are more
appropriate
phtest(fet3,ret3) # random effects are more appropriate

pcdtest(fet2) # not cross-sectional dependent
pcdtest(ret2) # not cross-sectional dependent
pcdtest(fet3) # not cross-sectional dependent
pcdtest(ret3) # not cross-sectional dependent

pbgtest(fet2) # there is serial correlation
pbgtest(fet3) # there is serial correlation
pbgtest(ret2) # there is serial correlation
pbgtest(ret3) # there is serial correlation
```

```
bptest(land ~ fce + factor(year), data = panel2, studentize=F) # there is heteroskedaticity
bptest(land ~ fce + fce2 + factor(year), data = panel2, studentize=F) # reject HO, thus
there is heteroskedaticity
bptest(land ~ fce + fce2 + fce3 + factor(year), data = panel2, studentize=F) # reject HO,
thus there is heteroskedaticity

bptest(ret3, studentize=F)

#### Recycled Panel Regression PANEL 3 ####

plm::is.pbalanced(panel3$country,panel3$year) # check if it is a balanced panel

# fixed effects
fe1 = plm(recyc ~ fce, data = panel3,index=c("country","year"),model="within") # recyc
summary(fe1, vcovHC)

# fixed effects with squared term
fe2 = plm(recyc ~ fce + fce2, data = panel3,index=c("country","year"),model="within")
summary(fe2, vcovHC)

# fixed effects with cubic term
fe3 = plm(recyc ~ fce + fce2 + fce3, data =
panel3,index=c("country","year"),model="within")
summary(fe3, vcovHC)

# random effects
re1 = plm(recyc ~ fce, data = panel3,index=c("country","year"),model="random")
summary(re1, vcovHC)

#random effects with squared term
re2 = plm(recyc ~ fce + fce2, data = panel3,index=c("country","year"),model="random")
summary(re2, vcovHC)

#random effects with cubic term
re3 = plm(recyc ~ fce + fce2 + fce3, data =
panel3,index=c("country","year"),model="random")
summary(re3, vcovHC)

# fixed effects with time
fet1 = plm(recyc ~ fce + factor(year), data=panel3, model="within")
summary(fet1,vcovHC)

fet2 = plm(recyc ~ fce + fce2 + factor(year), data=panel3, model="within")
summary(fet2,vcovHC) # with squared term.

fet3 = plm(recyc ~ fce + fce2 + fce3 + factor(year), data=panel3, model="within")
summary(fet3,vcovHC) # with cubic term

# random effects with time
ret1 = plm(recyc ~ fce + factor(year), data=panel3,
model="random",index=c("country","year"))
summary(ret1,vcovHC)
```

```
ret2 = plm(recyc ~ fce + fce2 + factor(year), data=panel3,
model="random",index=c("country","year"))
summary(ret2,vcovHC) # with squared term

ret3 = plm(recyc ~ fce + fce2 + fce3 + factor(year), data=panel3,
model="random",index=c("country","year"))
summary(ret3,vcovHC) # with cubic term

# panel diagnostics

cor(panel3$fce,panel3$recyc, method="pearson") # The correlation between the two
variables is 0.5564985.

pt1 = plm(recyc ~ fce + fce2 + fce3 + factor(year) + factor(country), data=panel3,
model="pooling")
plmtest(pt1, type=c("bp")) # reject HO, and state that there is a panel effect, therefore
pooled OLS is not appropriate
pt2 = plm(recyc ~ fce + fce2 + factor(year) + factor(country), data=panel3,
model="pooling")
plmtest(pt2, type=c("bp")) # there is a panel effect
pt3 = plm(recyc ~ fce + factor(year) + factor(country), data=panel3, model="pooling")
plmtest(pt3, type=c("bp")) # there is a panel effect

pFtest(ret1,re1) # there is a time effect
pFtest(fet3,fe3) # there is a time effect
pFtest(fet1,fe1) # there is a time effect
pFtest(ret3,re3) # there is a time effect
plmtest(fet1, c("time"), type=("bp")) # there is a time effect
plmtest(ret1, c("time"), type=("bp")) # there is a time effect
plmtest(fet3, c("time"), type=("bp")) # there is a time effect

adf.test(panel3$recyc, k=2)
# Because p-value < 0.05, therefore the series dos not have unit roots. This means that the
series is stationary
adf.test(panel3$fce, k=2) # stationary
adf.test(panel3$fce2, k=2) # stationary
adf.test(panel3$fce3, k=2) # stationary

# Model diagnostics
# All of these tests need to be performed individually for the models we would like to
compare

phtest(fet1,ret1) # fail to reject null (random) and state that the random effects are more
appropriate
phtest(fet3,ret3) # fixed effects are more appropriate

pcdtest(fet1) # not cross-sectional dependent
pcdtest(ret1) # not cross-sectional dependent
pcdtest(fet3) # not cross-sectional dependent
pcdtest(ret3) # not cross-sectional dependent

pbgtest(fet1) # there is serial correlation
```

```
pbgtest(fet3) # there is serial correlation
pbgtest(ret1) # there is serial correlation
pbgtest(ret3) # there is serial correlation

bptest(recyc ~ fce + factor(year), data = panel3, studentize=F) # there is heteroskedaticity
bptest(recyc ~ fce + fce2 + factor(year), data = panel3, studentize=F) # reject HO, thus
there is heteroskedaticity
bptest(recyc ~ fce + fce2 + fce3 + factor(year), data = panel3, studentize=F) # reject HO,
thus there is heteroskedaticity

#### Graphing against Regression Results ####

# Total

fun.1 <- function(x) 20.4389297 -3.4342419*x + 0.2043423*x^2
ggplot(data = panel1, aes(x=fce,y=total)) +
  geom_point(aes(color=country)) +
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Cubic Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Cubic"), fun = fun.1)

# Landfill

fun.1 <- function(x) -115.942251 +27.431529*x - 1.543502*x^2
ggplot(data = panel2, aes(x=fce,y=land)) +
  geom_point(aes(color=country)) +
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Cubic Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Cubic"), fun = fun.1)

fun.1 <- function(x) 1.2224e+03 -4.1782e+02*x + 4.7747e+01*x^2 - 1.8161e+00*x^3
ggplot(data = panel2, aes(x=fce,y=land)) +
  geom_point(aes(color=country)) +
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Cubic Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Cubic"), fun = fun.1)

# Recycling of Materials

fun.1 <- function(x) -1.0176e+03*x + 1.1106e+02*x^2 - -4.0295e+00*x^3
ggplot(data = panel3, aes(x=fce,y=recyc)) +
  geom_point(aes(color=country)) +
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Cubic Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Cubic"), fun = fun.1)

fun.1 <- function(x) -13.606188 + 1.866839*x
ggplot(data = panel3, aes(x=fce,y=recyc)) +
  geom_point(aes(color=country)) +
```

```
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Cubic Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Cubic"), fun = fun.1)

# Thesis Chapter Two
# Packaging Waste

require(readxl)
require(tidyverse)
require(ggpubr)
require(viridis)
require(plm)
require(lmtest)
require(tseries)

#### Descriptive Statistics ####

# All packaging waste generated for selected countries across years
packaging_waste_generated <- read_excel("Desktop/Indicators
Project/Descriptive/Transformed Data/packaging waste generated.xlsx")

all = packaging_waste_generated[,1:3] %>% rename(Region = Country) %>%
pivot_longer(-c(Region,Year), names_to = "type", values_to = "waste")
ggplot(data = all, aes(x=Year,y=waste,group=Region)) +
  geom_point(aes(color=Region),size=4) +
  geom_line(aes(color=Region)) +
  labs(x="Year",y="Packaging Waste in kg per capita", title = "All Packaging Waste
Generated over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

pwg = packaging_waste_generated %>% select(-"All packaging") %>% rename(Region =
Country) %>% pivot_longer(-c(Region,Year), names_to = "Type", values_to = "waste")
ggplot(data = pwg, aes(x=Year,y=waste,group=Region)) +
  geom_point(aes(color=Region,shape=Type),size=3) +
  geom_line(aes(color=Region)) +
  facet_grid(.~Type,scales = "free") +
  labs(x="Year",y="Packaging Waste in kg per capita", title = "Packaging Waste Generated
by Type over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Total Recovery
total_recovery <- read_excel("Desktop/Indicators Project/Descriptive/Transformed
Data/total recovery.xlsx")

allry = total_recovery[,1:3] %>% rename(Region = Country)%>% pivot_longer(-
c(Region,Year), names_to = "type", values_to = "waste")
allryplot=ggplot(data = allry, aes(x=Year,y=waste,group=Region)) +
  geom_point(aes(color=Region),size=4) +
  geom_line(aes(color=Region)) +
  labs(x="Year",y="Recovered Packaging Waste in kg per capita", title = "14A: All
Packaging Waste Recovered over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))
```

```
# Percentage Version
pr <- read_excel("Desktop/Indicators Project/Descriptive/Transformed Data/percentage
recovered.xlsx")
prall = pr %>% filter(Type=="All") %>% pivot_longer(-c(Type,year), names_to = "Region",
values_to = "waste")

prallplot = ggplot(data = prall, aes(x=year,y=waste,group=Region)) +
  geom_point(aes(color=Region),size=3) +
  geom_line(aes(color=Region)) +
  labs(x="Year",y="Percentage of Recovered Waste", title = "14B: All Recovered Packaging
Waste over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

ggarrange(allryplot,prallplot)

pwgry = total_recovery %>% select(-"All packaging") %>% rename(Region = Country)
%>% pivot_longer(-c(Region,Year), names_to = "Type", values_to = "waste")
ggplot(data = pwgry, aes(x=Year,y=waste,group=Region)) +
  geom_point(aes(color=Region,shape=Type),size=3) +
  geom_line(aes(color=Region)) +
  facet_grid(.~Type,scales = "free") +
  labs(x="Year",y="Recovered Packaging Waste in kg per capita", title = "Recovered
Packaging Waste by Type over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# PERCENTAGE VERSION
pro = pr %>% filter(Type!="All") %>% pivot_longer(-c(Type,year), names_to = "Region",
values_to = "waste")

ggplot(data = pro, aes(x=year,y=waste,group=Region)) +
  geom_point(aes(color=Region,shape=Type),size=3) +
  geom_line(aes(color=Region,linetype=Type)) +
  facet_wrap(~Type,scales = "free_y",ncol=2) +
  labs(x="Year",y="Percentage of Recovered Waste", title = "Recovered Packaging Waste
by Type over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Total Recycling

total_recycling <- read_excel("Desktop/Indicators Project/Descriptive/Transformed
Data/total recycling.xlsx")

allre = total_recycling[,1:3] %>% rename(Region = Country)%>% pivot_longer(-
c(Region,Year), names_to = "type", values_to = "waste")
a = ggplot(data = allre, aes(x=Year,y=waste,group=Region)) +
  geom_point(aes(color=Region),size=4) +
  geom_line(aes(color=Region)) +
  labs(x="Year",y="Recycled Packaging Waste in kg per capita", title = "16A: All Packaging
Waste Recycled over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))
```

```
pre <- read_excel("Desktop/Indicators Project/Descriptive/Transformed Data/percentage
recycled.xlsx")
preall = pre %>% filter(Type=="All") %>% pivot_longer(-c(Type,year), names_to =
"Region", values_to = "waste")

b = ggplot(data = preall, aes(x=year,y=waste,group=Region)) +
  geom_point(aes(color=Region),size=4) +
  geom_line(aes(color=Region)) +
  labs(x="Year",y="Percentage of Recycled Waste", title = "16B: Recycled Packaging Waste
by Type over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

ggarrange(a,b)

pwgre = total_recycling %>% select(-"All packaging") %>% rename(Region = Country)
%>% pivot_longer(-c(Region,Year), names_to = "Type", values_to = "waste")
ggplot(data = pwgre, aes(x=Year,y=waste,group=Region)) +
  geom_point(aes(color=Region,shape=Type),size=3) +
  geom_line(aes(color=Region)) +
  facet_grid(.~Type,scales = "free") +
  labs(x="Year",y="Recycled Packaging Waste in kg per capita", title = "Recycled Packaging
Waste by Type over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

# Percentage Version

preo = pre %>% filter(Type!="All") %>% pivot_longer(-c(Type,year), names_to = "Region",
values_to = "waste")

ggplot(data = preo, aes(x=year,y=waste,group=Region)) +
  geom_point(aes(color=Region,shape=Type),size=3) +
  geom_line(aes(color=Region,linetype=Type)) +
  facet_wrap(~Type,scales = "free_y",ncol=2) +
  labs(x="Year",y="Percentage of Recycled Waste", title = "Recycled Packaging Waste by
Type over Time", caption="Source: Eurostat") +
  theme(legend.position = "bottom",axis.text.x = element_text(angle = 90))

#### Preparing Data for Panel Regression ####

income1 <- read_excel("Desktop/Indicators Project/income.xlsx")
regions <- read_excel("Desktop/Indicators Project/regions.xlsx")
income = left_join(regions, income1, by = c("country"))

total <- read_excel("Desktop/Indicators Project/total.xlsx")
incomelong = income %>% pivot_longer(-c(country,region), names_to = "year", values_to =
"gdpo")
totallong = total %>% pivot_longer(-c(country), names_to = "year", values_to = "totalo")
totalw = left_join(totallong, incomelong, by = c("country","year"))
saveRDS(totalw, file = "totalw.rds")

paper <- read_excel("Desktop/Indicators Project/paper.xlsx")
paperlong = paper %>% pivot_longer(-c(country), names_to = "year", values_to =
"papero")
```

```
paperw = left_join(paperlong, incomelong, by = c("country","year"))
saveRDS(paperw, file = "paperw.rds")

plastic <- read_excel("Desktop/Indicators Project/plastic.xlsx")
plasticlong = plastic %>% pivot_longer(-c(country), names_to = "year", values_to =
"plastico")
plasticw = left_join(plasticlong, incomelong, by = c("country","year"))
saveRDS(plasticw, file = "plasticw.rds")

rm(list = ls())

#### Panel Regression Descriptives ####
# plm::is.pbalanced(panel1$country,panel1$year) # check if it is a balanced panel

plm::is.pbalanced(panel1$country,panel1$year) # check if it is a balanced panel
totalw <- readRDS("~/Desktop/Indicators Project/totalw.rds")
summary(totalw)

panel1 = totalw %>% mutate(gdp = log(gdpo),gdp2 =
log(gdpo)*log(gdpo),gdp3=log(gdpo)*log(gdpo)*log(gdpo),total=log(totalo),.keep="unused"
)

ggplot(data = panel1, aes(x=gdp,y=total)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(GDP) in current prices PPS per capita",y="ln(Total Packaging
Waste Generated) in kg per capita", title = "Total Packaging Waste vs Income",
caption="Source: Eurostat") + theme(legend.position = "bottom") +
scale_color_viridis(discrete=TRUE)

ggplot(data = panel1, aes(x=gdp,y=total)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(GDP) in current prices PPS per capita",y="ln(Total Packaging
Waste Generated) in kg per capita", title = "Total Packaging Waste vs Income by Country",
caption="Source: Eurostat") + theme(legend.position = "bottom") +
scale_color_viridis(discrete=TRUE) +
  facet_wrap(~country,scales = "free") +
  theme(legend.position = "none")

# PAPER
paperw <- readRDS("~/Desktop/Indicators Project/paperw.rds")
summary(paperw)

panel2 = paperw %>% mutate(gdp = log(gdpo),gdp2 =
log(gdpo)*log(gdpo),gdp3=log(gdpo)*log(gdpo)*log(gdpo),paper=log(papero),.keep="unus
ed")

ggplot(data = panel2, aes(x=gdp,y=paper)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(GDP) in current prices PPS per capita",y="ln(Paper and
Cardboard Packaging Waste Generated) in kg per capita", title = "Paper and Cardboard
Packaging Waste vs Income", caption="Source: Eurostat") + theme(legend.position =
"bottom") + scale_color_viridis(discrete=TRUE)
```

```
ggplot(data = panel2, aes(x=gdp,y=paper)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(GDP) in current prices PPS per capita",y="ln(Paper and
Cardboard Packaging Waste Generated) in kg per capita", title = "Paper and Cardboard
Packaging Waste vs Income by Country", caption="Source: Eurostat") + theme(legend.position
= "bottom") + scale_color_viridis(discrete=TRUE) +
  facet_wrap(~country,scales = "free") +
  theme(legend.position = "none")

# PLASTIC
plasticw <- readRDS("~/Desktop/Indicators Project/plasticw.rds")
summary(plasticw)

panel3 = plasticw %>% mutate(gdp = log(gdpo),gdp2 =
log(gdpo)*log(gdpo),gdp3=log(gdpo)*log(gdpo)*log(gdpo),plastic=log(plastico),.keep="unu
sed")

ggplot(data = panel3, aes(x=gdp,y=plastic)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Plastic Packaging Waste vs Income",
caption="Source: Eurostat") + theme(legend.position = "bottom") +
scale_color_viridis(discrete=TRUE)

ggplot(data = panel3, aes(x=gdp,y=plastic)) +
  geom_point(aes(color=country)) +
  labs(color="Country", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Plastic Packaging vs Income by Country",
caption="Source: Eurostat") + theme(legend.position = "bottom") +
scale_color_viridis(discrete=TRUE) +
  facet_wrap(~country,scales = "free") +
  theme(legend.position = "none")

#### Total Panel Regression PANEL1 ####

plm::is.pbalanced(panel1$country,panel1$year) # check if it is a balanced panel

# fixed effects
fe1 = plm(total ~ gdp + region, data = panel1,index=c("country","year"),model="within") #
total
summary(fe1, vcovHC)

# fixed effects with squared term
fe2 = plm(total ~ gdp + gdp2 + region, data =
panel1,index=c("country","year"),model="within")
summary(fe2, vcovHC)

# fixed effects with cubic term
fe3 = plm(total ~ gdp + gdp2 + gdp3 + region, data =
panel1,index=c("country","year"),model="within")
summary(fe3, vcovHC)

# random effects
```

```
re1 = plm(total ~ gdp + region, data = panel1,index=c("country","year"),model="random")
summary(re1, vcovHC)

#random effects with squared term
re2 = plm(total ~ gdp + gdp2 + region, data =
panel1,index=c("country","year"),model="random")
summary(re2, vcovHC)

#random effects with cubic term
re3 = plm(total ~ gdp + gdp2 + gdp3 + region, data =
panel1,index=c("country","year"),model="random")
summary(re3, vcovHC)

# fixed effects with time
fet1 = plm(total ~ gdp + factor(year) + region, data=panel1, model="within")
summary(fet1,vcovHC)

fet2 = plm(total ~ gdp + gdp2 + factor(year) + region, data=panel1, model="within")
summary(fet2,vcovHC) # with squared term.

fet3 = plm(total ~ gdp + gdp2 + gdp3 + factor(year) + region, data=panel1,
model="within")
summary(fet3,vcovHC) # with cubic term

# random effects with time
ret1 = plm(total ~ gdp + region + factor(year), data=panel1,
model="random",index=c("country","year"))
summary(ret1,vcovHC)

ret2 = plm(total ~ gdp + gdp2 + factor(year) + region, data=panel1,
model="random",index=c("country","year"))
summary(ret2,vcovHC) # with squared term

ret3 = plm(total ~ gdp + gdp2 + gdp3 + factor(year) + region, data=panel1,
model="random",index=c("country","year"))
summary(ret3,vcovHC) # with cubic term

# panel diagnostics

cor(panel1$gdp,panel1$total, method="pearson") # The correlation between the two
variables is 0.757032.

pt1 = plm(total ~ gdp + gdp2 + gdp3 + factor(year) + factor(country), data=panel1,
model="pooling")
plmtest(pt1, type=c("bp")) # reject HO, and state that there is a panel effect, therefore
pooled OLS is not appropriate
pt2 = plm(total ~ gdp + gdp2 + factor(year) + factor(country), data=panel1,
model="pooling")
plmtest(pt2, type=c("bp")) # there is a panel effect
pt3 = plm(total ~ gdp + factor(year) + factor(country), data=panel1, model="pooling")
plmtest(pt3, type=c("bp")) # there is a panel effect

pFtest(fet1,fe1) # reject HO, and state there is a time effect
```

```
pFtest(ret1,re1) # there is a time effect
pFtest(ret3,re3) # there is a time effect
plmtest(fe1, c("time"), type=("bp")) # do not reject HO and state there is no time effect
plmtest(re1, c("time"), type=("bp")) # there is no time effect

adf.test(panel1$total, k=2)
# Because p-value < 0.05, therefore the series dos not have unit roots. This means that the
series is stationary
adf.test(panel1$gdp, k=2)

# Model diagnostics
# All of these tests need to be performed individually for the models we would like to
compare

phtest(fet1,ret1) # fail to reject null (random) and state that the random effects is more
appropriate
phtest(fet3,ret3) # random effects is more appropriate
phtest(fe1,re1) # random effects is more appropriate
phtest(fe3,re3) # random effects is more appropriate

pcdtest(re1) # is cross-sectional dependent
pcdtest(re3) # is cross-sectional dependent
pcdtest(ret1) # not cross-sectional dependent

pbgtest(re1) # there is serial correlation
pbgtest(re3) # there is serial correlation
pbgtest(ret1) # there is serial correlation

bptest(total ~ gdp + factor(year), data = panel1, studentize=F) # fail to reject HO, thus
there's no heteroskedaticity
bptest(total ~ gdp + gdp2 + gdp3 + factor(year), data = panel1, studentize=F) # reject
HO, thus there is heteroskedaticity


#### Paper Panel Regression PANEL 2####

plm::is.pbalanced(panel2$country,panel2$year) # check if it is a balanced panel

# fixed effects
fe1 = plm(paper ~ gdp + region, data = panel2,index=c("country","year"),model="within")
# paper
summary(fe1, vcovHC)

# fixed effects with squared term
fe2 = plm(paper ~ gdp + gdp2 + region, data =
panel2,index=c("country","year"),model="within")
summary(fe2, vcovHC)

# fixed effects with cubic term
fe3 = plm(paper ~ gdp + gdp2 + gdp3 + region, data =
panel2,index=c("country","year"),model="within")
summary(fe3, vcovHC)
```

```
# random effects
re1 = plm(paper ~ gdp + region, data =
panel2,index=c("country","year"),model="random")
summary(re1, vcovHC)

#random effects with squared term
re2 = plm(paper ~ gdp + gdp2 + region, data =
panel2,index=c("country","year"),model="random")
summary(re2, vcovHC)

#random effects with cubic term
re3 = plm(paper ~ gdp + gdp2 + gdp3 + region, data =
panel2,index=c("country","year"),model="random")
summary(re3, vcovHC)

# fixed effects with time
fet1 = plm(paper ~ gdp + factor(year) + region, data=panel2, model="within")
summary(fet1,vcovHC)

fet2 = plm(paper ~ gdp + gdp2 + factor(year) + region, data=panel2, model="within")
summary(fet2,vcovHC) # with squared term.

fet3 = plm(paper ~ gdp + gdp2 + gdp3 + factor(year) + region, data=panel2,
model="within")
summary(fet3,vcovHC) # with cubic term

# random effects with time
ret1 = plm(paper ~ gdp + region + factor(year), data=panel2,
model="random",index=c("country","year"))
summary(ret1,vcovHC)

ret2 = plm(paper ~ gdp + gdp2 + factor(year) + region, data=panel2,
model="random",index=c("country","year"))
summary(ret2,vcovHC) # with squared term

ret3 = plm(paper ~ gdp + gdp2 + gdp3 + factor(year) + region, data=panel2,
model="random",index=c("country","year"))
summary(ret3,vcovHC) # with cubic term

# panel diagnostics

cor(panel2$gdp,panel2$paper, method="pearson") # The correlation between the two
variables is 0.757032.

pt1 = plm(paper ~ gdp + gdp2 + gdp3 + factor(year) + factor(country), data=panel2,
model="pooling")
plmtest(pt1, type=c("bp")) # reject HO, and state that there is a panel effect, therefore
pooled OLS is not appropriate
pt2 = plm(paper ~ gdp + gdp2 + factor(year) + factor(country), data=panel2,
model="pooling")
plmtest(pt2, type=c("bp")) # there is a panel effect
pt3 = plm(paper ~ gdp + factor(year) + factor(country), data=panel2, model="pooling")
plmtest(pt3, type=c("bp")) # there is a panel effect
```

```
pFtest(fet1,fe1) # reject HO, and state there is a time effect
pFtest(ret1,re1) # there is a time effect
plmtest(fe1, c("time"), type=("bp")) # do not reject HO and state there is no time effect
plmtest(re1, c("time"), type=("bp")) # there is no time effect

adf.test(panel2$paper, k=2)
# Because p-value < 0.05, therefore the series dos not have unit roots. This means that the
series is stationary
adf.test(panel2$gdp, k=2)

# Model diagnostics
# All of these tests need to be performed individually for the models we would like to
compare

phtest(fet1,ret1) # fail to reject null (random) and state that the random effects is more
appropriate
phtest(fe1,re1) # random effects is more appropriate

pcdtest(re1) # is cross-sectional dependent
pcdtest(ret1) # is not cross-sectional dependent

pbgtest(re1) # there is serial correlation
pbgtest(ret1) # there is serial correlation

bptest(paper ~ gdp + factor(year), data = panel2, studentize=F) # fail to reject HO, thus
there's no heteroskedaticity

#### Plastic Panel Regression PANEL 3####

plm::is.pbalanced(panel3$country,panel3$year) # check if it is a balanced panel

# fixed effects
fe1 = plm(plastic ~ gdp + region, data = panel3,index=c("country","year"),model="within")
# plastic
summary(fe1, vcovHC)

# fixed effects with squared term
fe2 = plm(plastic ~ gdp + gdp2 + region, data =
panel3,index=c("country","year"),model="within")
summary(fe2, vcovHC)

# fixed effects with cubic term
fe3 = plm(plastic ~ gdp + gdp2 + gdp3 + region, data =
panel3,index=c("country","year"),model="within")
summary(fe3, vcovHC)

# random effects
re1 = plm(plastic ~ gdp + region, data =
panel3,index=c("country","year"),model="random")
summary(re1, vcovHC)

#random effects with squared term
```

```
re2 = plm(plastic ~ gdp + gdp2 + region, data =
panel3,index=c("country","year"),model="random")
summary(re2, vcovHC)

#random effects with cubic term
re3 = plm(plastic ~ gdp + gdp2 + gdp3 + region, data =
panel3,index=c("country","year"),model="random")
summary(re3, vcovHC)

# fixed effects with time
fet1 = plm(plastic ~ gdp + factor(year) + region, data=panel3, model="within")
summary(fet1,vcovHC)

fet2 = plm(plastic ~ gdp + gdp2 + factor(year) + region, data=panel3, model="within")
summary(fet2,vcovHC) # with squared term.

fet3 = plm(plastic ~ gdp + gdp2 + gdp3 + factor(year) + region, data=panel3,
model="within")
summary(fet3,vcovHC) # with cubic term

# random effects with time
ret1 = plm(plastic ~ gdp + region + factor(year), data=panel3,
model="random",index=c("country","year"))
summary(ret1,vcovHC)

ret2 = plm(plastic ~ gdp + gdp2 + factor(year) + region, data=panel3,
model="random",index=c("country","year"))
summary(ret2,vcovHC) # with squared term

ret3 = plm(plastic ~ gdp + gdp2 + gdp3 + factor(year) + region, data=panel3,
model="random",index=c("country","year"))
summary(ret3,vcovHC) # with cubic term

# panel diagnostics

cor(panel3$gdp,panel3$plastic, method="pearson") # The correlation between the two
variables is 0.757032.

pt1 = plm(plastic ~ gdp + gdp2 + gdp3 + factor(year) + factor(country), data=panel3,
model="pooling")
plmtest(pt1, type=c("bp")) # reject HO, and state that there is a panel effect, therefore
pooled OLS is not appropriate
pt2 = plm(plastic ~ gdp + gdp2 + factor(year) + factor(country), data=panel3,
model="pooling")
plmtest(pt2, type=c("bp")) # there is a panel effect
pt3 = plm(plastic ~ gdp + factor(year) + factor(country), data=panel3, model="pooling")
plmtest(pt3, type=c("bp")) # there is a panel effect

pFtest(fet1,fe1) # no time effect
pFtest(ret1,re1) # no time effect
pFtest(fet3,fe3) # no time effect
pFtest(ret3,re3) # no time effect
plmtest(fe3, c("time"), type=("bp")) # do not reject HO and state there is no time effect
```

```
plmtest(re3, c("time"), type=("bp")) # there is no time effect

adf.test(panel3$plastic, k=2)
# Because p-value < 0.05, therefore the series dos not have unit roots. This means that the
series is stationary
adf.test(panel3$gdp, k=2)

# Model diagnostics
# All of these tests need to be performed individually for the models we would like to
compare

phtest(fe1,re1) # random effects is more appropriate
phtest(fe3,re3) # fixed effects is more appropriate

pcdtest(re1) # is not cross-sectional dependent
pcdtest(fe3) # is not cross-sectional dependent

pbgtest(re1) # there is serial correlation
pbgtest(fe3) # there is serial correlation

bptest(plastic ~ gdp + gdp2 + gdp3 + factor(year), data = panel3, studentize=F) # fail to
reject HO, thus there's no heteroskedaticity
bptest(plastic ~ gdp + factor(year), data = panel3, studentize=F) # no heteroskedaticity

# Graphing model 27 and 28
fun.1 <- function(x) -101.018596*x + 10.131925*x^2 -0.335831*x^3
cubic = ggplot(data = panel3, aes(x=gdp,y=plastic)) +
  geom_point(aes(color=country)) +
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Cubic Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Cubic"), fun = fun.1)

fun.2 <- function(x) -3.331390 + 0.643917*x
linear = ggplot(data = panel3, aes(x=gdp,y=plastic)) +
  geom_point(aes(color=country)) +
  labs(color="Key", x="ln(GDP) in current prices PPS per capita",y="ln(Plastic Packaging
Waste Generated) in kg per capita", title = "Linear Result", caption="Source: Eurostat/Own
Calculation") + theme(legend.position = "", text = element_text(size = 20)) +
geom_function(aes(colour = "Linear"), fun = fun.2)

ggarrange(cubic,linear)

# Comparing correlation
cor(paperw$papero,paperw$gdpo, method="pearson") #0.6305646
cor(panel2$gdp,panel2$paper,method="pearson") #0.7649613

cor(plasticw$plastico,plasticw$gdpo, method="pearson") #0.6538363
cor(panel3$gdp,panel3$plastic,method="pearson") #0.7090483

cor(totalw$totalo,totalw$gdpo,method="pearson") #0.6890545
cor(panel1$gdp,panel1$total,method="pearson") #0.757032
```

```
# Thesis Chapter Three
# Waste Trade Network Analysis

# Libraries
library(readr)
library(tidyverse)
library(igraph)
library(readxl)
library(countrycode)
library(RColorBrewer)
library(plotrix)
library(viridis)
library(ggpubr)
library(ggsci)
library(cowplot)
set.seed(1234)

#### Descriptive Statistics ####

summary(import_2020$QUANTITY_IN_100KG)
summary(export_2020$QUANTITY_IN_100KG)

euim = import_2020 %>% group_by(REPORTER) %>% summarise(import =
sum(QUANTITY_IN_100KG))
euex = export_2020 %>% group_by(REPORTER) %>% summarise(export =
sum(QUANTITY_IN_100KG))
euexpart = export_2020 %>% group_by(PARTNER) %>% summarise(export =
sum(QUANTITY_IN_100KG))
df = euim %>% left_join(euex,by="REPORTER") %>%
  mutate(reporter = word(REPORTER,1)) %>%
  # mutate(net.export = export - import) %>%
  select(-c(REPORTER)) %>%
  rename(Import = import,Export = export) %>% pivot_longer(-c(reporter), names_to =
"Type", values_to = "quantity") %>%
  mutate(tons = quantity * 100 / 1000)

ggplot(df, aes(fill=Type, y=tons, x=reporter)) +
  geom_bar(position="dodge", stat="identity") +
  labs(color="", x="Country",y="Paper and Cardboard Waste in metric tons", title = "Trade
of Waste Paper and Cardboard by Country and Type ", caption="Source: Eurostat") +
theme(legend.position = "bottom",axis.text.x=element_text(angle = 90))

#### Data Preparation ####

# IMPORT NETWORK
import_2020 <- read_excel("Downloads/import 2020.xlsx")
import = import_2020 %>% mutate(reporter = word(REPORTER,1), partner =
word(PARTNER,1)) %>%
  mutate_at("partner", str_replace, "Viet", "Vietnam") %>%
  rename(quantity = QUANTITY_IN_100KG) %>%
  select(c(reporter,partner,quantity)) %>%
  filter(quantity >= median(quantity),) %>%
  mutate_at("partner", str_replace, "United", "United States") %>%
```

```
  mutate_at("partner", str_replace, "Russian", "Russia") %>%
  mutate_at("partner", str_replace, "Costa", "Costa Rica") %>%
  mutate_at("partner", str_replace, "North", "Macedonia") %>%
  mutate_at("partner", str_replace, "Moldova,", "Moldova") %>%
  mutate_at("partner", str_replace, "Dominican", "Dominican Rep") %>% relocate(partner)

importg = graph.data.frame(import, directed = TRUE)

# EXPORT NETWORK
export_2020 <- read_excel("Downloads/export 2020.xlsx")
export = export_2020 %>% mutate(reporter = word(REPORTER,1), partner =
word(PARTNER,1)) %>%
  mutate_at("partner", str_replace, "Viet", "Vietnam") %>%
  rename(quantity = QUANTITY_IN_100KG) %>%
  select(c(reporter,partner,quantity)) %>%
  filter(quantity >= median(quantity)) %>%
  mutate_at("partner", str_replace, "United", "United States") %>%
  mutate_at("partner", str_replace, "Russian", "Russia") %>%
  mutate_at("partner", str_replace, "Costa", "Costa Rica") %>%
  mutate_at("partner", str_replace, "North", "Macedonia") %>%
  mutate_at("partner", str_replace, "Moldova,", "Moldova") %>%
  mutate_at("partner", str_replace, "Dominican", "Dominican Rep") %>%
  mutate_at("partner", str_replace, "Hong", "Hong Kong") %>%
  mutate_at("partner", str_replace, "Saudi", "Saudi Arabia") %>%
  mutate_at("partner", str_replace, "Korea,", "South Korea") %>%
  mutate_at("partner", str_replace, "Faroe", "Faroe Islands") %>%
  mutate_at("partner", str_replace, "Syrian", "Syria")

exportg = graph.data.frame(export, directed = TRUE)

# FULL IM/EX Network
import_renamed = import %>% rename(from = partner, to = reporter)
export_renamed = export %>% rename(from= reporter, to = partner)
imex = bind_rows(export_renamed,import_renamed)
imexg = graph.data.frame(imex,directed = T)

# Finding the subregions + color them in

importg = graph.data.frame(import, directed = TRUE)
import.countries = V(importg)$name
subregion = countrycode(sourcevar = import.countries,origin = "country.name",destination =
"un.regionsub.name")
import.att = as.data.frame(cbind(import.countries,subregion))
import.att = import.att %>% mutate_all(~replace(., is.na(.), "Northern Africa"))
importg =
set.vertex.attribute(importg,"subregion",index=V(importg),value=factor(import.att$subregion))
colrs <- terrain.colors(9)
V(importg)$color <- colrs[V(importg)$subregion]

export.countries = V(exportg)$name
subregion = countrycode(sourcevar = export.countries,origin = "country.name",destination =
"un.regionsub.name")
export.att = as.data.frame(cbind(export.countries,subregion))
```

```
export.att = export.att %>% mutate_all(~replace(., is.na(.), "Eastern Asia"))
exportg =
set.vertex.attribute(exportg,"subregion",index=V(exportg),value=factor(export.att$subregion)
)
colrs <- terrain.colors(13)
V(exportg)$color <- colrs[V(exportg)$subregion]

imex.countries = V(imexg)$name
subregion = countrycode(sourcevar = imex.countries,origin = "country.name",destination =
"un.regionsub.name")
imex.att = as.data.frame(cbind(imex.countries,subregion))
imex.att = imex.att %>% mutate_all(~replace(., is.na(.), "Eastern Asia"))
imexg =
set.vertex.attribute(imexg,"subregion",index=V(imexg),value=factor(imex.att$subregion))
colrs <- terrain.colors(13)
V(imexg)$color <- colrs[V(imexg)$subregion]

#### PLOTS ####

# Import

par(mfrow=c(1,2))
plot(importg,vertex.label.cex=.5,edge.arrow.size=.1, layout=layout.kamada.kawai,
main="2020 EU Import Network of Waste Paper and Cardboard", xlab="Source:
Eurostat",vertex.size=10,edge.width=log(E(exportg)$quantity/1000))

# Export
plot(exportg,vertex.label.cex=.5,edge.arrow.size=.1, layout=layout.kamada.kawai,
main="2020 EU Export Network of Waste Paper and Cardboard", xlab="Source:
Eurostat",vertex.size=10,edge.width=log(E(exportg)$quantity/1000))

# Full
par(mfrow=c(1,1))
plot(imexg,vertex.label.cex=.5,edge.arrow.size=.1, layout=layout.kamada.kawai,
main="2020 EU Full Trade Network of Waste Paper and Cardboard", xlab="Source:
Eurostat",vertex.size=10,edge.width=log(E(exportg)$quantity/1000))

#### Network Statistics ####

ecount(importg) #320 edges
vcount(importg) #52 vertices
ecount(exportg) # 436 edges
vcount(exportg) # 68 vertices
ecount(imexg) # 756 edges
vcount(imexg) # 80 vertices

graph.density(importg) #0.121
graph.density(exportg) #0.096
graph.density(imexg)   #0.120

average.path.length(importg) #2.044706
average.path.length(exportg) #2.005727
average.path.length(imexg) #2.185355
```

```
transitivity(importg) #0.4678197
transitivity(exportg) #0.4113017
transitivity(imexg) #0.4213187

diameter(importg) #4
diameter(exportg) #4
diameter(imexg) #4

#### Centrality Measures ####

max(degree(importg)) # Netherlands 46
max(evcent(importg)$vector) # Germany 1
max(betweenness(importg, weights = 1/(E(importg)$quantity))) # Netherlands 700
max(closeness(importg, weights = 1/(E(importg)$quantity))) # Netherlands 0.0007

max(degree(exportg)) # Netherlands 57
max(evcent(exportg)$vector) # Netherlands 1
max(betweenness(exportg, weights = 1/(E(exportg)$quantity))) # Germany 1231
max(closeness(exportg, weights = 1/(E(exportg)$quantity))) # Italy 1.819214e+02

max(degree(imexg)) # Netherlands 103
max(evcent(imexg)$vector) # Germany 1
max(betweenness(imexg, weights = 1/(E(imexg)$quantity))) # Germany 2016
max(closeness(imexg, weights = 1/(E(imexg)$quantity))) # Iceland 0.001136355

#### Louvain Community Detection ####

importgu = graph.data.frame(import, directed = F)
iml = cluster_louvain(importgu,weights=E(importg)$quantity)

plot(iml,importgu,node.size=0.01,main="Louvain Community Detection ~ Import
Network",xlab="Source: Eurostat")
imldf = cbind(iml$membership,iml$names)
View(imldf)

exportgu = graph.data.frame(export, directed = F)
exl = cluster_louvain(exportgu,weights=E(exportg)$quantity)

plot(exl,exportgu,node.size=0.01,main="Louvain Community Detection ~ Export
Network",xlab="Source: Eurostat")
exldf = cbind(exl$membership,exl$names)
View(exldf)

imexgu = graph.data.frame(export, directed = F)
imexl = cluster_louvain(imexgu,weights=E(imexg)$quantity)
plot(imexl,imexgu,node.size=0.01,main="Louvain Community Detection ~ Full Trade
Network",xlab="Source: Eurostat")

imexldf = cbind(imexl$membership,imexl$names)
View(imexldf)

#### Dendogram ####
```

```
ima <- as_adjacency_matrix(importgu, type = "both", names = TRUE,sparse = FALSE)
imd = hclust(as.dist(1-cor(ima),upper=T),method="complete")
plot(imd,cex=0.5,main="Dendogram of the Import Network", hang=-1,xlab="Source:
Eurostat")

exa <- as_adjacency_matrix(exportgu, type = "both", names = TRUE,sparse = FALSE)
exd = hclust(as.dist(1-cor(exa),upper=T),method="complete")
plot(exd,cex=0.5,main="Dendogram of the Export Network", hang=-1,xlab="Source:
Eurostat")

imexa <- as_adjacency_matrix(imexgu, type = "both", names = TRUE,sparse = FALSE)
imexd = hclust(as.dist(1-cor(imexa),upper=T),method="complete")
plot(imexd,cex=0.5,main="Dendogram of the Full Trade Network", hang=-1,xlab="Source:
Eurostat")

#### Structural Equivalence ####

dlayout = layout.fruchterman.reingold(importgu)
elayout = layout.fruchterman.reingold(exportgu)
flayout = layout.fruchterman.reingold(imexgu)

par(mfrow=c(1,2))
# import
plot(importg,vertex.label.cex=.5,edge.arrow.size=.1, layout=dlayout, main="2020 EU Import
Network of Waste Paper and Cardboard", xlab="Source:
Eurostat",vertex.size=5,edge.width=(E(importgu)$quantity)^-0.2)
plot(importgu,edge.width=(E(importgu)$quantity)^-
0.2,vertex.color=cutree(imd,k=4),vertex.label.cex = .5, main='Structural Equivalence in the
Import Network',vertex.size=5,edge.color="grey",layout=dlayout, xlab="Source: Eurostat")

# Export
plot(exportg,vertex.label.cex=.5,edge.arrow.size=.1, layout=elayout, main="2020 EU Export
Network of Waste Paper and Cardboard", xlab="Source:
Eurostat",vertex.size=10,edge.width=log(E(exportg)$quantity/1000))
plot(exportgu,edge.width=(E(exportgu)$quantity)^-
0.2,vertex.color=cutree(imd,k=4),vertex.label.cex = .5, main='Structural Equivalence in the
Export Network',vertex.size=5,edge.color="grey",layout=elayout, xlab="Source: Eurostat")

# Full
par(mfrow=c(1,1))
plot(imexg,vertex.label.cex=.5,edge.arrow.size=.1, layout=layout.kamada.kawai,
main="2020 EU Full Trade Network of Waste Paper and Cardboard", xlab="Source:
Eurostat",vertex.size=10,edge.width=log(E(exportg)$quantity/1000))




plot(exportgu,edge.width=(E(exportgu)$quantity)^-
0.2,vertex.color=cutree(imd,k=4),vertex.label.cex = .5, main='Structural Equivalence in the
Export Network',vertex.size=5,edge.color="grey",layout=elayout)
```

```
plot(imexgu,edge.width=(E(imexgu)$quantity)^-0.2,vertex.color=cutree(imd,k=4),vertex.label.cex = .5, main='Structural Equivalence in the Full Trade Network',vertex.size=5,edge.color="grey",layout=flayout)
```