Students *and* Public Transport

A Multilevel Analysis

Master's Thesis

Urban, Port, and Transportation Economics

Academic Year 2014 – 2015

Bauyrzhan Murzamadiyev

Student Number: 327995

Thesis supervisor: Jan-Jelle Witte

Word Count: 16117

Abstract

There is an extensive list of research done on modal split, yet few take into consideration the effect of students. This paper attempts to identify the effect of a student population within a city has on its city's public transport share in 52 cities across Europe. Using a multilevel model, the 52 cities are nested into 48 NUTS3 regions and 7 countries. The findings of the multilevel model are that: an increase in (i) the share of students, (ii) commuting time, and (iii) population density increases the share of public transport; (iv) an increase in GDP per capita and (v) in area decreases the public transport share; (vi) and lastly there seems to be a differing effect of public transport costs across NUTS3 regions.

Acknowledgment

This thesis has come a long way since its inception, first from the initial ideas of using a multinomial logit/probit model to analyze student travel behavior to this multilevel analysis. There were hills and valleys on this journey and I could not have done it without two people, my thesis supervisor Jan-Jelle Witte and my fiancée Gabriela Veselinova.

I would like to thank my thesis supervisor Jan-Jelle for providing guidance during the writing process of my thesis. Despite the summer holiday vacation season, you were able to dedicate some time to me and help me with my research. Your advice was highly appreciated.

And to my best friend, soul mate, and fiancée Gabriela Veselinova, thank you for giving me critical feedback and also for being very patient with me. I know it is difficult to organize our wedding, especially with so many other things happening around us at the same time, so thank you my love.

Lastly I would like to thank the Learning Environment for Multilevel Methods and Applications (LEMMA). Your modules on multilevel analysis were the backbone of the quantitative analysis. Your in-depth explanations of the modeling allowed for a full understanding of the process and what is exactly happening. The model is no longer some black box, but a tool in the arsenal of quantitative analysis.

Table of Contents

List of Figures

Chapter 1: Introduction

The driving force of modal split, or the proportion of a certain form of transportation, is the interest of many research papers. Whether they are focusing on individual aspects such as car ownership (*Balcombe et al, 2004; Buehler, 2011; Cervero, 2002; Chen et al, 2008; Frank, 1994; Kim and Ulfarsson, 2008; Kitamura, 2009; Paulley et al, 2006; Pinjari et al, 2007; Sabir, 2011; Scheiner, 2010*) or even external factors such as the built environment (*Schwanen, 2002; Scheiner, 2010; Susilo and Maat, 2007*), all are attempts to justify the reasons why individuals prefer a certain mode of transportation. The common conclusions of transport research determine that high population densities are affiliated with a greater use of public transport (PT), essentially due to the greater utilization levels attained because of a larger amount of riders.

Research on this topic generally diverges into two ways of analyzing the matter (*Santos et al, 2013*). The first being an introspective approach, which has a very intuitive argument: the choices one makes are a consolidation of many individual aspects, taking into consideration one's income, age, and having children just to mention a few, the decisions one makes are a reflection of these individual factors. On the other hand, the extrospective approach has also been alluded to, but to a lesser extent. This has to do with how cities, provinces, or even countries affect the individual, instead of his or her own personal factors.

Despite the plentiful literature on modal split, the effect of the share of students on travel behavior has rarely been studied directly. Some papers insert a student variable without any justification, giving the impression of an impulsive thought, others address the topic in an indirect manner, such as increasing active modes of transportation when commuting to university (*Shannon et al, 2005*). Despite the increasing trend to use PT, partly due to benefits for students such as a free transportation card (*Brown et al, 2001, Brown et al 2003; Litman, 2004; Shannon et al, 2005*), some studies have overlooked the PT factor altogether, instead using it as a proxy for cycling and walking (*Rodrigez and Joo, 2004*). Furthermore, with the typical use of discrete choice models for modal split studies in previous papers, interpretations can be difficult. These models give insight on the relative direction of the effect with no indication on the absolute magnitude, which is why a multilevel (ML) analysis is proposed in this paper. An ML model has a unique feature of combining econometric techniques by including both a fixed part and a random part of the modeling. More interestingly, the random part includes level effects, so it is possible to combine the introspective and extrospective approach in one.

The characteristics of students add an interesting aspect to the research. They can be generally characterized as having low or no income. Thus, trying to save money has been seen as a primary motivation (*Shannon et al, 2006*). Consequently, students tend to be very price sensitive (*Brown et al, 2003*), which additionally explains the rather large surplus of student users of PT when a free transportation policy is adopted (*Brown et al, 2003; Litman, 2004; Shannon et al, 2006*). Students are also not part of the long-term residential population (*Brown et al, 2003*). This could lead to irregular traveling patterns when comparing to the 'nine to five' employee. With these in consideration, one can deduce that students could have different behavioral patterns when it comes to travel. The amount of students has been used as a variable for several purposes. One popular use is a proxy representing the proportion of students over the whole population. This allows it to embody the share of students within a city and can express the "friendliness" towards slower transportation modes such as PT, cycling, and even walking (*Santos et al, 2013*). This relationship between students and slower modes of transportation can be limited, as studies have shown that density of an area also plays an influential role. This leads to a greater reliance on personal vehicles (*Litman, 2005*). A similar trend is seen in *Shannon et al, 2006*, where approximately 40% of students are inclined to use personal vehicles when distances are larger than one kilometer in Perth's University of Western Australia (UWA). PT use has exploded up to 200% within the first year of the introduction of free PT for students in many countries, followed by subsequent growth in the following years (*Brown et al, 2001*). This puts an interesting perspective on PT use and the dependence on the student population. On a wider context, this research may help cities better understand the position they are in with respects to their student population and their PT system. For example, if a city has a large student population, then it may be inclined to keep fare prices low to keep the demand stable.

This paper will focus on finding the effect students have on the PT, more specifically, to what extent does the number of students have an effect on the proportion of PT use on a city level, while controlling for variables such as PT cost, commuting time, and more. This study will attempt to confirm that there is a significant “student effect” that influences the PT within a city.

The structure of this paper is as follows: relevant research concerning modal split and the travel behavior of students will be reviewed in chapter 2. Chapter 3 will include the methodological approach. Chapter 4 will assess the data with descriptive statistic. In Chapter 5, a multilevel model will be built and results analyzed. Finally, concluding remarks and limitations will be discussed in chapter 6, with possible recommendation for future research.

Chapter 2: *Literature Review*

This chapter establishes the theoretical foundation of the research. This will provide the proper contextual basis in evaluating the effect of the student population on the PT. This is done through the evaluation of relevant works on modal split and students travel behavior within cities. The order of the literature review is as follows: first, the importance of a European wide study is emphasized. Second, modal split is introduced, which is followed by a focus on students. Lastly, policies that encourage PT use are examined.

2.1 European Cities

Although an all encompassing theory on travel behavior is tempting to make, there are a lot of factors that would need to be accounted for. In the transportation field, many studies have tried to compare European travel behaviors to that of the United States (US) (*Schwanen, 2002; Buehler, 2011; Van Acker et al, 2007*), yet the conclusions are clear; despite the commonalities, there are still factors that are difficult to control for that play a role, such as policies or the underlying culture. In multilevel modeling, this would be the presence of a composition effect. *Schwanen, 2002* states that there are four crucial dissimilarities influencing the transportation behavior between Europe and the US. These dissimilarities can add to this composition effect and make it difficult for any contextual analysis to be made.

First there is a noticeable physical difference between European and American cities. For example, European cities are geographically smaller and older historically than the US. As such, the cities are inclined to be of a smaller size and the concentration of cities through out Europe tends to be higher. With higher densities, there is greater demand for land in Europe, which leads to the second reason, urban planning policies. As land becomes scarcer, the need to manage urban development becomes critical. As a result, it appears that most European nations have controlled the overwhelming growth of urban areas. This is especially the case when considering the Dutch "Bestemmingsplan", which is responsible for the land use planning. From this it is evident that every plot of land within the Netherlands is accounted for. Third, the context of Europe's economic circumstance is different to the US. Lastly, there is a large culture difference that may have an added composition effect. Subsequently, it could affect the travel behavior of individuals, leading to the observation of lesser car dependence, ownership, and use compared to the US. Furthermore, PT and slower modes of transport are far more dominant in Europe than the US (*Kenworth and Laube, 1999; Schwanen, 2002*).

The reasons why Europe differs from the US by *Schwanen, 2002* are evident in other studies as well. Inline with the first reason of *Schwanen, 2002* and *Van Acker et al, 2007* focus on historic city centers is emphasized. With some European cities centers originating from the 14th century, the inherited labyrinth like roads deters driving, whereas US cities are characterized as being grid-like strengthen auto dependency. Additionally, with the smaller spatial scale of Europe and the preference for compact development, slower modes and more active modes are stimulated (*Van Acker et al, 2007*), supporting the second reason of *Schwanen, 2002*. The four reasons is evident in *Buehler, 2011*, where auto dependent nations, Germany and the US, were compared. It is clear why it can be useful to compare the two countries, as they have a very large and strong automotive industry, but despite controlling for socio-economic, demographic, and spatial variables in their model, compared to Americans, it is more probable that Germans use PT and slower modes of transport. It is later explained in *Buehler, 2011* that these differences are captured in variables exogenous to their model such as policies and cultural differences. Thus posing a challenge for policy makers because what was effective in one country would not have the same results in the other. More specifically, when it comes to transportation behavior influences, Germans are less sensitive to changes in population density and access to PT, compared to Americans, who, despite living in higher density and proximity to PT, still choose to drive (*Buehler, 2011*).

There are some discrepancies noted in *Schwanen, 2002* that even within Europe, there are differences in travel behavior, but these behaviors are more inline with each other than reaching some global convergence as suggested by "The World City Hypothesis" in *Friedmann, 1986*, hinting at the prevalence of a

'European culture'. This idea is also put forth in *Hill and Kim, 2000* where a comparison between the development of three global cities, New York, Tokyo, and Seoul was made. The conclusion reached in that study was that, despite all three cities are considered as global cities, they do not converge onto one level, but rather cluster. The example in *Hill and Kim, 2000*, being that Seoul's development is more inline with the development of Tokyo and not New York, suggests the presence of an 'Asian culture'. With this in mind, not only would it be problematic to have different regional data on a global scale, because different factors are emphasized differently from culture to culture (*Schwanen, 2002*), but also the paths of development would not be the same (*Beuhler, 2011; Hill and Kim, 2000*). To minimize this composition effect, data on the European level will be analyzed.

2.2 General Modal Split

Before going in-depth on the behavior of student travel, it is important to understand overall modal split and modal split studies. The most available data and most common independent variables of modal split studies usually include the use of private cars, PT, bicycles, and walking. Occasionally when there is the opportunity to conduct a survey, other modes are included, such as motorcycles, taxis, and subdivisions in PT (bus, tram, and subway). *Figure 1* summarized the main points of each study because of the immense amount of literature on the topic. The summary is largely based on *Santos et al, 2013*, where various modal split studies are reviewed. *Figure 1* comprises of the average result of the relationship studies, showing the prominent conclusions of all studies on a topic. This way it is easier to get a contextual feeling toward modal split and the various variables researched. With a quick observation of *Figure 1*, it should be clear that most of the literature focuses on the influences of driving and PT use unlike motorcycling, cycling, and walking, which lack overall research on the associations. The relevant relationships will be discussed in further detail below.

Like mentioned in the beginning of this paper, there are two general methods of analyzing the influences on modal split, the introspective and extrospective approach. These approaches are not only reflected in the many variables each study is testing against the modal split, but also the specific angle each study has. An example of an individual aspect is age. With possible changes in preferences over time, a change in the travel behavior is also anticipated (*Santos et al, 2013*). Car use seems to peak between the ages 35 to 65 (*Dargay and Hanly, 2007*; Van *Acker et al, 2007*). This could be explained by the fact that people tend to have a family and subsequently children. With the onset of children, PT use goes down due to the greater convenience of a car (*Santos et al, 2013*). The stigma to continue using the car seems to carry on to the later ages as the negative association with the more active modes of transport can explain a decrease of health that comes with age (*Newman et al, 2009*), emphasizing the car's door-to-door convenience. Not to mention, if elderly people do decide to drive, the distance traveled is shorter than middle-aged people (*Schwanen et al, 2004*; *Van Acker et al, 2007*). *Santos et al, 2013* confirms this finding with the counter example from *Sabir, 2011* and *Kim and Ulfarsson, 2008* as they found that PT use declines in later years, especially for short journeys.

Figure 1
Prominent conclusions reached by various authors on modal split

Independent Variable	Conclusions				
	Driving	PT	Motorcycling	Cycling	Walking
Age	+/–	–/=	–	–	–
Income	+	–	–	–	+
Car Ownership	+	–	–	–	+/–
Students Population	?	+	+	+	+
Resident Population	?	+	?	?	?
Population Density	–	+	+	+	+
City Size	–	+	?	+/–	+/–
Sidewalk Availability	?	?	?	+	+
Land Use	–	+	?	+	+
Policy	–	+	?	?	?
GDP per capita	+	+	–	–	+
Number of Buses	?	+	?	?	?
PT Fare	+	–	?	?	?
PT Frequency	–	+	?	?	?
Trip Distance	+	+	+/–	+/–	–
Rain	+	+	–	–	–

Key: "+" represents a positive relationship, "–" represents a negative relationship, "=" represents no relationship, "?" represents that the relationship was not researched. Mixes of the symbols, such as "+/– " represent a mixed relationship where there are more or less an equal amount of studies observing a positive and negative relationship. As such, "–/=" represents a mixed relationship where there are more or less an equal about of studies observing negative or no relationship.

Income also plays a role in modal split. Low-income groups tend to be more inclined to be PT dependent (*Litman, 2004*). As incomes rise, there is more expendable income, leading to the purchase of a car (*Santos et al, 2013*). Likewise, car ownership increases the use of the car and simultaneously reduces the chances of using PT (*Santos et al, 2013*).

Population measures tend to favor PT use and with a clear logic behind; as densities increase, higher utilization of the PT can be reached, thus in turn creating the opportunity for growth in the PT network (*Schwanen, 2002*) and better organization (*Van Acker et al, 2007*). Most of the literature reflects the tendency of higher population densities, not only having a positive relationships with PT use, but also reduces car use because of the increasing amount of congestion (*Beuhler, 2011*; *Cervero, 2002*; *Frank and Pivo, 1994*; *Litman, 2005*; *Santos et al,* 2013; *Schwanen,* 2002; *Van Acker et al, 2007*; *Zhang, 2007*). Although an increase population density seems to positively affect PT, the scientific community seems to have a rather mixed feeling towards the effects on non-motorized travel, such as biking and walking. Some studies conclude population density encourages non-motorized travel (*Santos et al, 2013*; *Zhang, 2007*), in the sense that it attracts new users. Other studies conclude it is at the cost of non-motorized travel (*Schwanen, 2002*), where these active modes of travel compete more with themselves.

Very closely related to population density is the size of a city. City size has been shown to increase PT use and decrease car use (*Santos et al, 2013*; *Schwanen, 2002*; *Van Acker et al, 2007*), but as *Schwanen, 2002* emphasizes, at the expense of non-motorized modes of travel. This could be due to the increasing distances between commuting to work from home that the slower modes such as biking and walking cannot cover efficiently (*Schwanen, 2002*). As a result, commuting times tend to be longer in larger cities (*Van Acker et al, 2007*). This is especially the case in Europe because some housing policies may restrict relocation initiatives (*Schwanen, 2002*).

Sidewalk availability and land use are very closely related to each other because in essence they are a measure of how the land is organized. This similarity also stretches to how they affect modal split, as seen in *Figure 1*, where they behave similarly, both promoting non-motorized modes of transport (*Rodriguez and Joo, 2004*). Although there are not many studies that take into account sidewalk availability, it perhaps can be assumed that it behaves in a similar fashion as land use, depending on how the land use variable is defined. A way to measure land use is through a proxy or ratio that represents the diversity of the land. Land use yields analogous effects on modal split as increasing densities (*Frank and Pivo, 1994*; *Litman, 2005*; *Van Acker et al, 2007*). These proxies can include a number of diverse types of land use such as distinguishing between residential, industrial, and work areas (*Litman, 2005*). *Litman, 2005* continues to explain that an increase in the land use variables creates "urban villages", where the decreased distances of certain areas allow for non-motorized travel. Frequently, land use variables are ignored because of assumptions that travel time and costs capture the effects of land use on travel behavior in the long run, but it has been empirically proved through models that land use has an independent influence on travel behavior, especially significant in the short-run (*Zhang, 2007*). Not only do land use variables have explanatory power, but also excluding them can result in omitted variable bias by affecting other variables such as travel time and cost (*Rodriguez and Joo, 2004*). *Rodriguez and Joo, 2004* also challenge the explanatory power of including the presence of sidewalks as they have rather ambiguous results in other previous research.

Policies play an important role in transport behavior as housing policies, as mentioned earlier, can prevent urban sprawl, and other policies can affect the attractiveness of certain modes of transport, such as heavy taxation on carbon emissions. Policies do not seem to have overflowing, but rather a direct affect on what the specific policy is aiming at. For example, job-housing policies are ineffective to air quality initiatives (*Frank and Pivo, 1994*) and decreasing the costs to travel by PT would most likely cause a rise in PT use and a simultaneous decrease in car use (*Santos et al, 2013*). Thus it is difficult to present policy in *Figure 1* as each policy tends to have a direct effect, in that the specific goal set are usually achieve it. This would mean that increasing the costs of car use would most likely decrease car use and etcetera. This directness of policies stretches to higher PT fares and PT frequency, where lower fares and higher frequencies correspond to higher PT use and lower car use (*Santos et al, 2013*).

An increase in income or GDP per capita has primarily been associated with an increased amount of driving (*Santos et al, 2013*). The reasoning may be due to the perception of the car as a symbol of status. When a person has enough income, the trend is to purchase a car. With car ownership, the chances of using the car are significantly larger than if the person does not own one (*Balcombe et al, 2004; Buehler, 2011; Cervero, 2002; Chen et al, 2008; Frank, 1994; Kim and Ulfarsson, 2008; Kitamura, 2009; Paulley et al, 2006; Pinjari et al, 2007; Sabir, 2011; Scheiner, 2010*). Most studies subsequently relate an increase in income with a decrease in PT use. Only *Kitamura, 2009* found an increase in PT use, but this was done at the household level.

Rain is an interesting variable that has not been tested as frequently as the others mentioned. With *Sabir, 2011*, rain seems to have a positive relationship with PT use, which is rather strange when one may expect people to use PT and also non-motorized modes of transport less because of having to walk in unfavorable weather conditions (*Sumalee et al, 2011*). However, *Sabir, 2011* did not control for the specific details of PT, overlooking whether there is cover provided cover for PT users, as seen in subways or bus stops with roofs. When controlling for these additional variables, *Sumalee et al, 2011* concluded that indeed, with increasing amount of rain, people tend to use PT where cover is provided from adverse weather. Because this further detail of PT are not easy to obtain, this study would expect results more inline with *Sabir, 2011* than *Sumalee et al, 2011*.

Literature shows that there are many things affecting people when they decide to travel, be it owning a car or even a chance of rain. By understanding the various influences the modal split may have, a foundation is developed to investigate further on how students may behave.

2.3 Student Travel Behavior

Now that there is a familiarity of the general trends in modal split, the focus can be brought onto the student dimension. Distinctive individual characteristics or the "personality dimension" has been seen to influence the perception of various factors of travel behavior (*Van Acker et al, 2007*). For example, offering a discounts on PT may be more attractive for students than car owners. *Kitamura et al, 1997* and *Bagley and Mokhtarian, 2002*, expanded this concept by taking into account individual lifestyles. As a result, their research concluded that the type of lifestyle explained the most variation when it came to travel behavior, while controlling for land use and other traditional variables. This lifestyle effect could be stretched to students and would explain their difference in travel behavior.

Although students have also been positively associated with positive use of motorcycles and slower modes of transport, student travel behavior is primarily associated with PT use (*Litman, 2005*; *Santos et al, 2013*). This is much more apparent in Europe as cities have higher densities and are more oriented towards the PT network, which also promotes walking (*Santos et al, 2013*; *Schwanen, 2002*). Car dependence seems to be the strongest in low-density cities. *Litman, 2005* explains this finding, where an educational institution can provide schooling for students on a larger range in low-density cities than in higher density cities because of the larger distances of low-density cities. Because of the spread being so large, it forces students to drive, unlike more dense cities, where students may be able to bike or walk. A prime example of this would be Perth, where almost half of the student population at the University of Western Australia (UWA) drove to the university (*Shannon et al, 2006*). This is why it is very important to control for density, otherwise there will be an unequal weight on the modal split, making it incomparable.

To understand student behavior properly, it is important to understand the motives of students. In the research of *Shannon et al, 2006*, they explored a way to increase active modes of transport in Perth, which involved understanding the motives and barriers of students. What was found was that students' highest priority was to save money. Furthermore, because Perth is a very auto dependent city, with almost half of the student body driving, students also had found it essential to find a parking spot (*Shannon et al, 2006*). The price sensitivity of students is also supported by *Litman, 2005*, where although students are seen as PT dependent, they are not price insensitive like other PT dependent users. This would make options like driving a car rather costly. According to *Shannon et al, 2006*, travel time is the most significant concern for students regardless of any differences to distance. Taking into account the relatively higher densities of Europe, the slower modes of transport are also advantageous to students due to the relatively closer distances, making biking and walking a real alternative cost and time wise. This is quite an interesting finding because even if the student is located walking distance to the university, travel time is still the greatest concern.

With the underlying trend of an increasing PT use with students, it raises the question of how much do the students actually contribute to the PT share, when taking into account discounts policies. Discount policies can take many different forms. The most prevalent is the subsidization of PT costs for students via a discount. When investigating further onto the various European cities, it is evident that a partial discount on the fare price is the most popular option. The less common option is to either not provide any type of discount for students or to fully subsidize student PT travel. These types of policies seem to significantly motivate students to use PT as it saves them money. In Perth, it was seen to be the strongest element that encouraged students to use PT, also including those who biked or walked (*Shannon et al, 2006*). What was the most astonishing finding from *Shannon et al, 2006* was that despite Perth's auto dependency, there was a willingness to forego driving if reasonable alternatives are offered. Other evidence from the US has shown the success of a similar policy of BruinGo, which had an increase of student PT use up to 200% from its launch in 2001 (*Brown et al, 2001*), where almost a third of students were new PT users and the rest previous drivers (*Brown et al, 2003*). With BruinGo, there was an overall outcome of a shift from driving to using PT and other slower modes of transport (*Brown et al, 2003*). With these increases in PT user, it creates a cycle of growth and development, where there is an expansion of service (*Brown et al, 2003*). This could balance out the relationship of car ownership with PT, if the PT network can provide comparable benefits to car transport.

There are three major outcomes of BruinGo that *Brown et al, 2003* goes into further detail. First is that, more can be invested to better services because of the increase in revenues of the PT provider due to the increased riders. With these improvements, it would draw the interests of additional riders. Second, as BruinGo is offered to everyone, this builds interest to find more about it. Ridership can increase with this increased familiarity of the services provided. The last outcome of *Brown et al, 2003* goes into the long-term aspect, with an increased location decision of student housing. Where previously they were bound to live in the proximity of the university, will now be able benefit from the various available BruinGo stations and have a larger variety to choose from. Thus with these types of policies, it is not just a short run increase in ridership, but it can stretch into the long run. Additional benefits include a decrease in the demand for parking lots, facilitating in making the university more attractive, and making attending university more affordable (*Brown et al, 2001*). With all these benefits stressed, most of the analysis on this topic view how important PT is for students, but in this paper the reverse is analyzed. Because full utilization of PT is very important for the PT providers, what will be the effect of students when controlling for all these variables. Could it be that students actually have no incentive to use PT if all else kept equal?

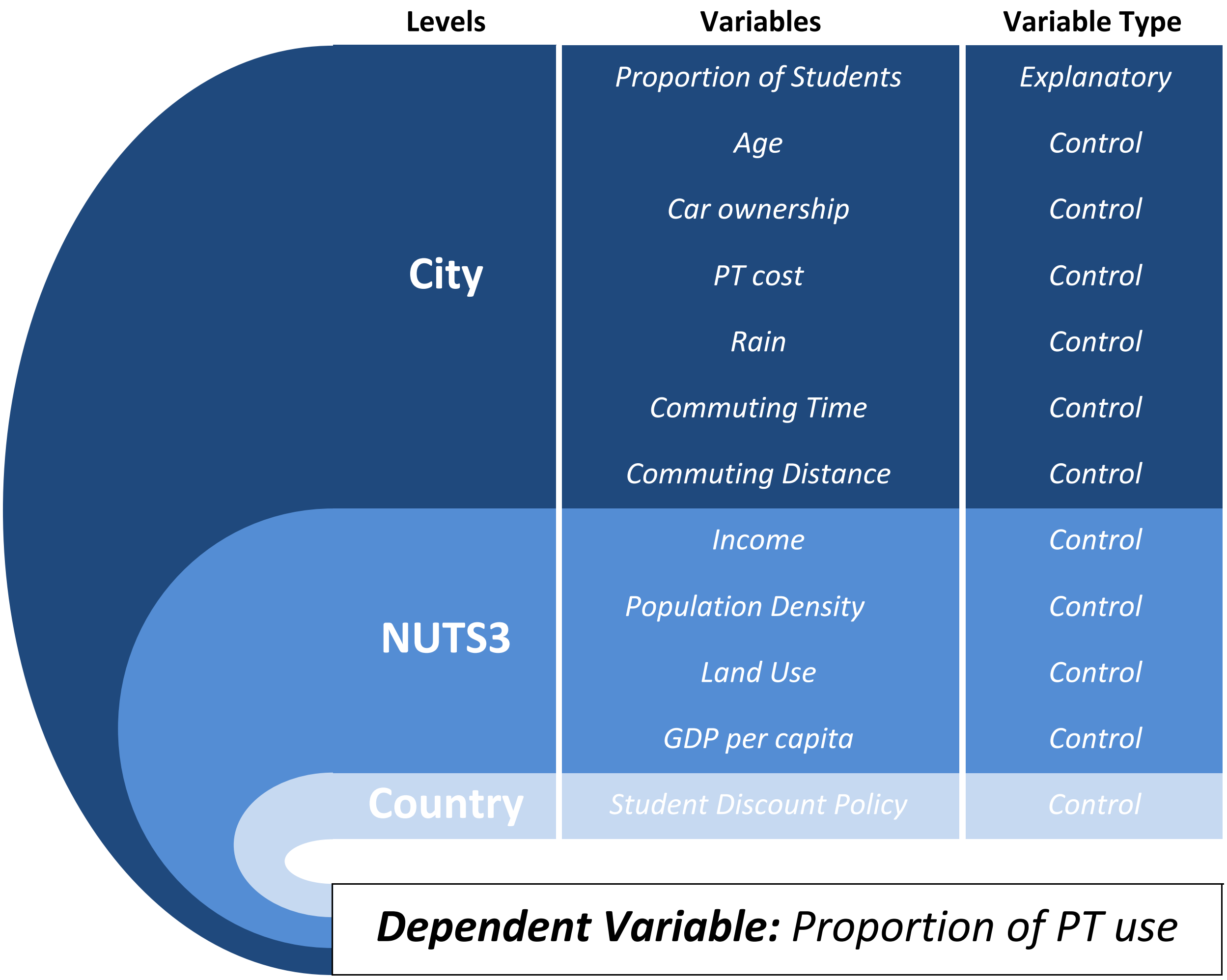
Chapter 3: Methodology

This research will use cross-sectional data where observations are nested within 3 levels: city, NUTS3, and country. Because each observation is from a different city, the city level is technically the individual level. Ordinary Least Square (OLS) regression is inappropriate mainly due to group dependence. In OLS, group dependence would cause very low standard errors because it would be ignoring the group aspect of the data. Although the standard errors can be corrected for by using the White standard errors, multilevel (ML) analysis is still preferred over OLS for two reasons. First, ML analysis is more efficient as it uses a within and between dimension across the different levels, which can avoid the use of an excessive amount of dummy variables. Second, ML analysis is more flexible than OLS. This is because ML models can allow for random slopes on different levels and complex covariance structures, which can explain heterogeneity in the model.

The concept behind ML modeling is to control for the composition effects or the individual characteristics, so that the contextual effect or the group characteristics can be revealed. This can be done through analyzing the group variances and level effects that are captured by the model.

The process of analysis includes first describing data, then the model developed, and finally the model's outcomes are analyzed. This method is based on the methods of the Learning Environment for Multilevel Methods and Applications (LEMMA) "*Module 11: Three-Level Multilevel Models*" (*Lecklie, 2013*). A conceptual model is made to better understand the structure of the ML model represented in *Figure 2*. With an ML analysis, the model will be built step by step, with the inception of an intercept only model. Subsequently, variables will be added and tested with the Likelihood Ratio (LR) test on whether they add more explanatory power. First the city variables will be added, followed by the NUTS3 level and country level variables.

Figure 2
Conceptual Model



Taking the literature review into consideration, this paper has 3 hypotheses to test:

Because students are cost conscious, it could be expected that they will choose the cheapest form of transport. Of course walking and cycling are free, but these have a limited range. Thus, the first hypothesis is that an increase in the student population leads to an increase in PT use within a city.

Hypothesis 1: Cities with a higher proportion of students increase the share of PT use.

Because different regions may have different proportion of students, it would be speculative to assume that the student effect on PT is fixed across regions and that each region may have a same magnitude of this effect. This leads to the second hypothesis that there is a presence of heterogeneity in the student effect across NUTS3 regions.

> ***Hypothesis 2a:*** There is heterogeneity in the student effect across NUTS3 regions

After proving the heterogeneity of the student variable, the magnitude of this heterogeneity can be analyzed through its covariance structure. This would give insight on the degree of the regional effect of students. In turn, hypothesis 2b is that NUTS3 regions with a lower than average PT use would be more sensitive to an increase in the student population.

> ***Hypothesis 2b:*** With an increase of the students share, NUTS3 regions with a lower than average PT use share would have a larger increase in PT use than NUTS3 regions with a higher than average PT use share.

The last hypothesis takes into account the various national policies that subsidize student travel, divided into full, partial, or no discount. The hypothesis is that a full discount policy for students would have the largest effect on PT use, compared to a partial and no discount policy.

> ***Hypothesis 3:*** Countries that offer a full discount for students will have a greater share of PT use than countries with partial or no discount policy

Chapter 4: *Data*

In this chapter, the data will be discussed. All of the data has been collected from the European Union statistical office, Eurostat. In total, 14 datasets from Eurostat were compiled, reshaped, and merged using Stata. The most challenging part was matching the different city codes with their corresponding NUTS3 code. This was because the city codes have a different type of syntax unlike the composite nature of the NUTS syntax, where the first two letters represent the country code and the subsequent numbers represent regions.

Furthermore, Stata is the main statistical software used in this research. Most of the data ranges from the year 1990 until 2014. In this research, only the most recent observation from each city is used, but still some cities do not have updated figures. The full list of cities can be seen in *Appendix 5.* Thus, caution should be taken in the interpretations for some cities such as Zürich, Nantes, Winterthur, and Biel because some variables have not been updated. This can be problematic for variables that change dramatically over the years, such as PT use. On the other hand, there are variables that are quite stable over the years, such as area. The reason for selecting the most recent observations of cities is because the data does not lend itself to take the time aspect into account in this multilevel model. More specifically, each city only includes a maximum of one observation per year, thus nesting observations per year would be useless.

Discount policy data was collected through interviews with students from the 20 European countries that are part of this research. The interviewees were personal acquaintances that had been studying for a minimum of 1 year in the specific country and were also nationals of it. The variables *income* and *rain* were not included in the modeling due to a lack of data. There were no observations left for the *income* variable after the merging process, thus GDP per capita is used as a proxy towards income. Moreover, the variables *commutedist* and *rain* have a lot more missing values relative to other variables. As a consequence, it removes too many observations in a model when including it in the calculations.

4.1 Descriptive Statistics

It is important to check the dataset for any abnormalities such as outliers as they will affect the consecutive statistical outputs. Although outliers are not necessarily a bad thing, it is still important to be aware of them, as their characteristics may not be applicable to the whole sample. A graph matrix is made with all the variables to see whether there are any abnormalities in the data. The full output is presented in *Appendix 1*, where some observations require further attention. The observations that need to be investigated are presented in *Figure 3* below. This graph matrix displays a scatter plot of each variable with one another over, making outliers very easy to spot. By labeling the outliers, it allows a closer examination of which specific observations are outliers. These are presented in *Figure 4*. These outlier observations point to Hungarian cities. With a closer look to both city data, it seems that they have been recorded incorrectly. The Hungarian data for PT use seems incorrectly recorded because, where other countries have percentages and not exceeding 100%, Hungary is reported to have around 75,000% of PT use compared to other modes of transport. This was consistent with the other Hungarian cities, and thus the observations for Hungary was dropped due to clear error. With all said and done, this shows the importance of further investigating outliers, occasionally they are mistakes in the data and do not represent the reality.

Figure 3

Graph matrix between variables

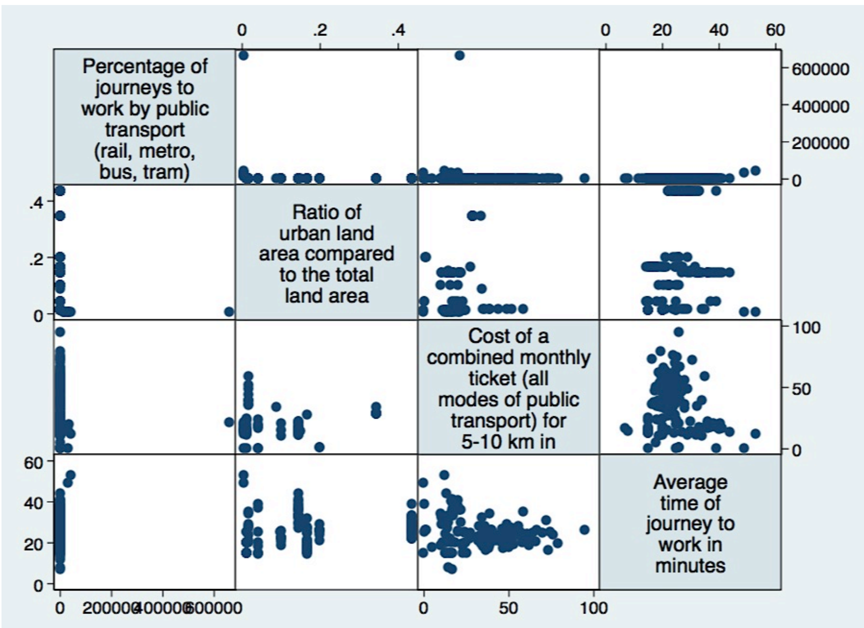
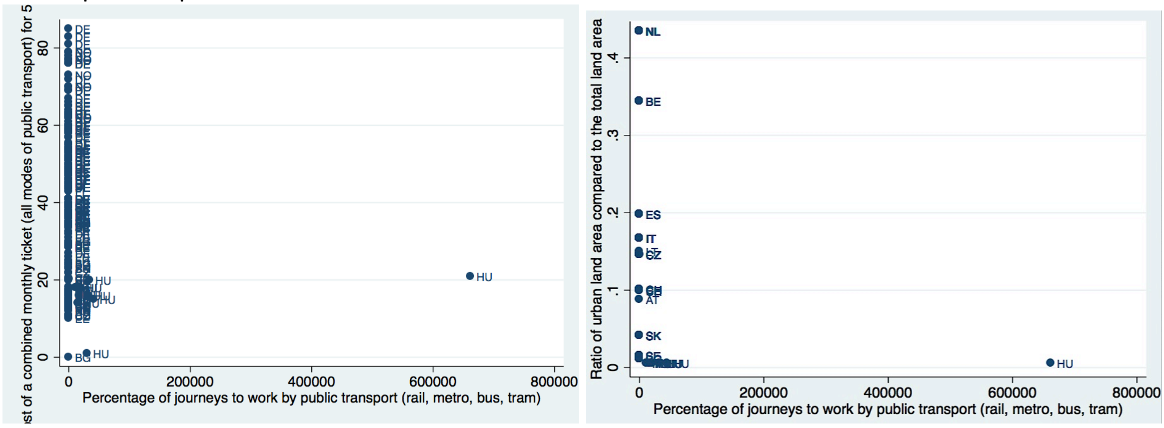


Figure 4

Scatter plots of possible outliers



Now that the outliers have been taken care of, descriptive statistics will be looked at. With the use –des– and –sum–, the data is generally described and summarized. These results are presented in *Appendix 2* and *Appendix 3*. Because this is hierarchical data, there are no special commands such as –xtdes– and –xtsum–. *Appendix 2* shows that the dataset has 680 observations and 25 variables, one of which is a categorical variable *policy*. This variable has three categories. The first is "Full Discount", representing a fully subsidized PT for students, such as seen in the Netherland and Germany. These are mainly organized on a national level. The second, "Partial Discount", representing the presence of a student discount for PT fare, these are generally 50% off the regular price and are mainly city specific. The last category is "No Discount", which means that there is no discount offered to students, such places include Switzerland. As such, this categorical variable has been create into a 3 dummies *fulldisc*, *partdisc*, and *nodisc*.

Figure 5

Tabulated Policy Dummy Variables

Levels	Full Discount	Partial Discount	No Discount	Total
City	34	486	160	**680**
NUTS3	20	305	151	**476**
Country	2	15	3	**20**

The data is summarized in *Appendix 3*, indicating the number of observations, mean value, standard deviation, the minimum and maximum. Because the –sum– command summarizes numerical inputs, string variables such as *nationcode*, *nuts3code*, and *citycode* display zero observations, mean, standard deviation, minimum, and maximum. This table also acts as a confirmation of the data, such as the years, the minimum is 1990 and the maximum is 2012 and that the dummy variables are indeed binary. The dummy variables can be tabulated to examine their distribution across levels, which are displayed in *Figure 5*. *Figure 5*, acts as a confirmation of the number of observations in each level because there can only be one type of policy per country. Thus, each level total represents the number of cities, NUTS3 regions, and countries respectively. As such, the data contains 680 city observations that are nested in 476 different NUTS3 regions. These NUTS3 regions are nested in 20 different countries. The data also reflects the nature of the policy and confirms that a partial discount policy is the most prevalent. Although not required for a multilevel analysis, it is important to note this trend reflects the unbalanced nature of the policy data. This can be further confirmed by Stata's –codebook– command where its output is on *Appendix 4*. Here it shows that indeed this data set has 680 cities, 476 NUTS3 regions, and 20 countries.

Next the dependent and the independent variables will be evaluated. By checking the distribution of the dependent variable *ptuse* through a histogram, a visual representation is made in *Figure 6*. It should be noted that the distribution of *ptuse* is skewed to the right and is not normally distributed. It is not a requirement for the dependent variable to be normally distributed in multilevel analysis, therefore it should not cause any statistical inconsistencies. More importantly, the residuals should be normally distributed to make any inferences with the model, but this will be discussed later in the paper.

Because the main purpose of this paper is to find the effect of the student population on PT and essentially whether student discount policies affect this, it can be interesting to calculate the average levels of PT use for each different type of policy and see how they differ. The expectation is that with a free PT policy for students, PT use should be the highest, subsequently followed by the partial discount policy, leaving the lowest PT use with a no discount policy. A bar graph is plotted in *Figure 7* confirming the earlier expectation of a higher PT use on average with a free PT policy. Because *ptuse* is an index of the proportion of PT use over driving, cycling, and walking, it is a percentage. Thus, by looking at the bar graph in *Figure 7*, there is a difference of approximately 10 percentage points between a free policy and a discount policy. What is also interesting to see is that a discount policy and no policy have relatively same mean PT use, instead of a clear difference like with the free and discount policy. In summary, a free PT scheme may have the largest impact on the levels of PT use, with marginal differences between a discount and no discount schemes.

Figure 6

Histogram of the dependent variable *ptuse*

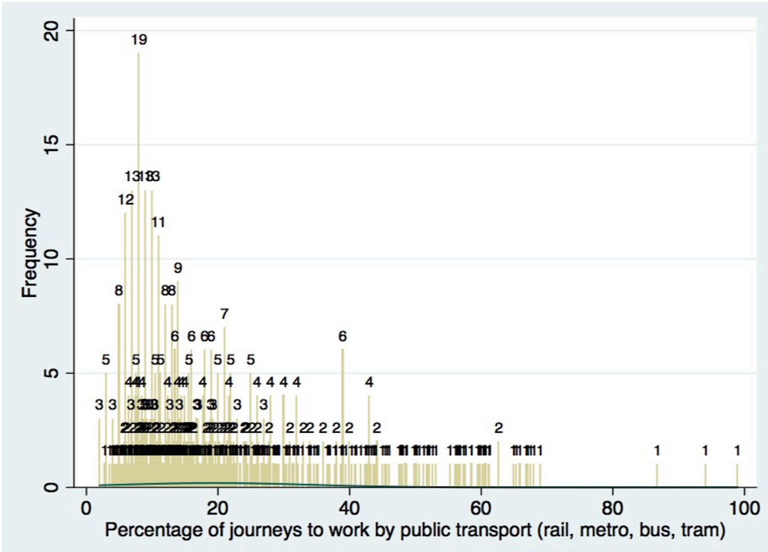
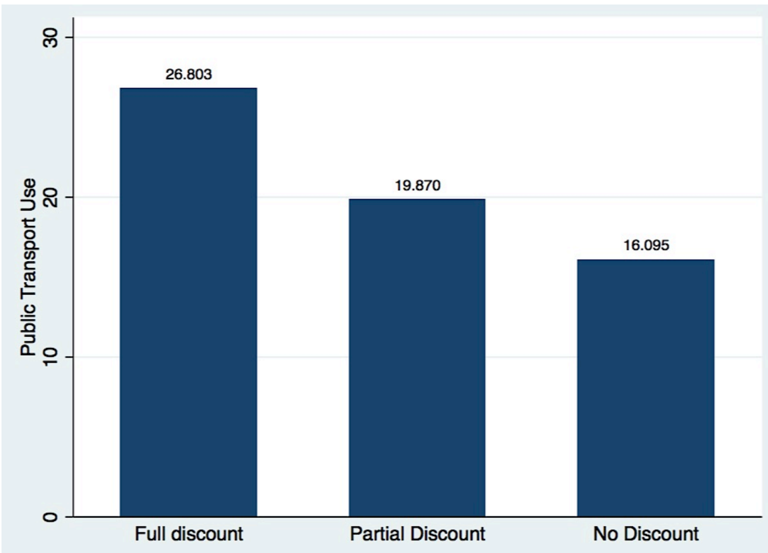


Figure 7

Average PT use over the different discount policies



Multicollinearity is also very important to check. An exact linear relationship with the independent variables can be problematic as it leads to imprecise estimates. In *Figure 8*, a correlation matrix is created. This paper will use a 0.70 limit to the correlations. All of the independent variables seem to not be too correlated with each other and being below the established 0.70 limit. Although the variables are below the limit, *gdppc* and *ptcost* come very close to the 0.70 correlation limit. This is not unexpected as the PT costs could be capturing some income effects that are represented in GDP per capita.

Figure 8

Correlation matrix between the independent variables

	student	ptcost	carown~p	commut~e	commut~t	age65p	gdppc	popden	area	landuse
student	1.0000									
ptcost	-0.0649	1.0000								
carownership	-0.2928	-0.1721	1.0000							
commutetime	0.1959	0.1308	-0.5146	1.0000						
commutedist	-0.1949	0.3395	0.1750	0.2938	1.0000					
age65p	-0.4837	0.2564	0.2580	-0.1481	0.4688	1.0000				
gdppc	-0.0319	0.6932	-0.4704	0.4780	0.6010	0.2870	1.0000			
popden	0.0445	-0.0644	0.0246	0.4328	0.4966	0.2515	0.1908	1.0000		
area	0.0945	0.3899	-0.2727	-0.0003	0.1191	-0.1229	0.4511	-0.1864	1.0000	
landuse	0.0238	-0.4218	-0.2495	0.2066	0.3186	0.2588	0.2303	0.3387	-0.0373	1.0000

Chapter 5: Results and Analysis

Unlike in OLS regression, in ML analysis, it is important to build up the model starting an intercept only base model. Adding explanatory variables to the base model and conducting LR tests to confirm that the added subsequent variables indeed provide additional explaining power is the procedure taken in this paper to build the final model.

5.1 Intercept Only Model

The first step is to have an intercept model only to provide as a base, which would include city, NUTS3, and country level random effects. This would mean that only the dependent variable is included across the three level data. Formally, this base model is written as follows:

$$ptuse_{ijkl} = \beta_0 + w_l + v_{kl} + u_{jkl} + e_{ijkl}$$

Where: $w_l \sim N(0, \sigma_w^2)$
$v_{kl} \sim N(0, \sigma_v^2)$
$e_{ikl} \sim N(0, \sigma_e^2)$

Where *ptuse*$_{ijkl}$ is the percentage of modal split that is PT within a European city. Each city observation i (i = 1,…,680) is in a NUTS3 region k (k = 1,…,476) in a country l (l = 1,…,20). The intercept β_0 is the mean percentage of PT use throughout all countries l, with an effect w_l, NUTS3 regions k, with an effect v_{kl}, and finally the single city observation residual error term e_{ijkl}. There is also an assumption that all the ML effects and residual errors are independent and follow a normal distributed that has a mean of zero and a constant variance.

The model is built by using Stata's –xtmixed– command that uses a maximum likelihood estimation which can be likened to a 'badness' to fit *id es,* the more negative it is, the better fitting the model is. This model is written as follows in Stata: *xtmixed ptuse || country: || nuts3:, mle variance*, where *ptuse* is the dependent variable and the following *country*, *nuts3*, and *city* and are the levels descending from the highest level to the lowest level. The *mle variance* represents the maximum likelihood estimation. The output of this model is displayed in *Figure 9*.

Stata optimizes the model until it converges, where at that point it is able to give an output. In this model, it converges in three iterations. Stata provides us with three tables that this paper will go into further detail. Other interesting output from Stata includes the number of observations, which in this case is 680. This number represents the number of observations captured by this model. In the upcoming models, the number of observations will drop because the observations captured by the model are different to the datasets total observations. This is a sign of an unbalanced dataset, as not all the observations have data for some variables. This becomes a challenged when adding more variables, as the observation count will decrease and running an ML model becomes more difficult to converge.

Figure 9

Base model output of *–xtmixed ptuse || country: || nuts3:, mle– variance–*

Group Variables	**No. of Groups**			
Country	20		No. of observations:	680
NUTS3	476		Log likelihood:	-2513.6251

Variables	**Coefficient**	**95% Confidence Interval**	
intercept	22.62909*	16.21365	29.04453

Level Variance	**Estimate**	**VPC**	**95% Confidence Interval**	
Country	192.4892*	64.20%	98.0882	377.7426
NUTS3	68.85077*	22.96%	57.6141	82.27897
Residual	38.46908*	12.83%	32.64437	45.33308

LR test vs. linear regression:	chi2(2)= 567.53	Prob > chi2 = 0.0000

*Statistically significant at the 0.05 level

There are three main components to the output of *Figure 8*. First is the data on the group variables, presenting all of the three levels included in the model: *country* and *NUTS3*. The *city* level is not shown because the number of observations represents the number of cities, as each observation is from a different city. It also displays the number of groups within each level, accounting for 20 countries, and 476 NUTS3 regions.

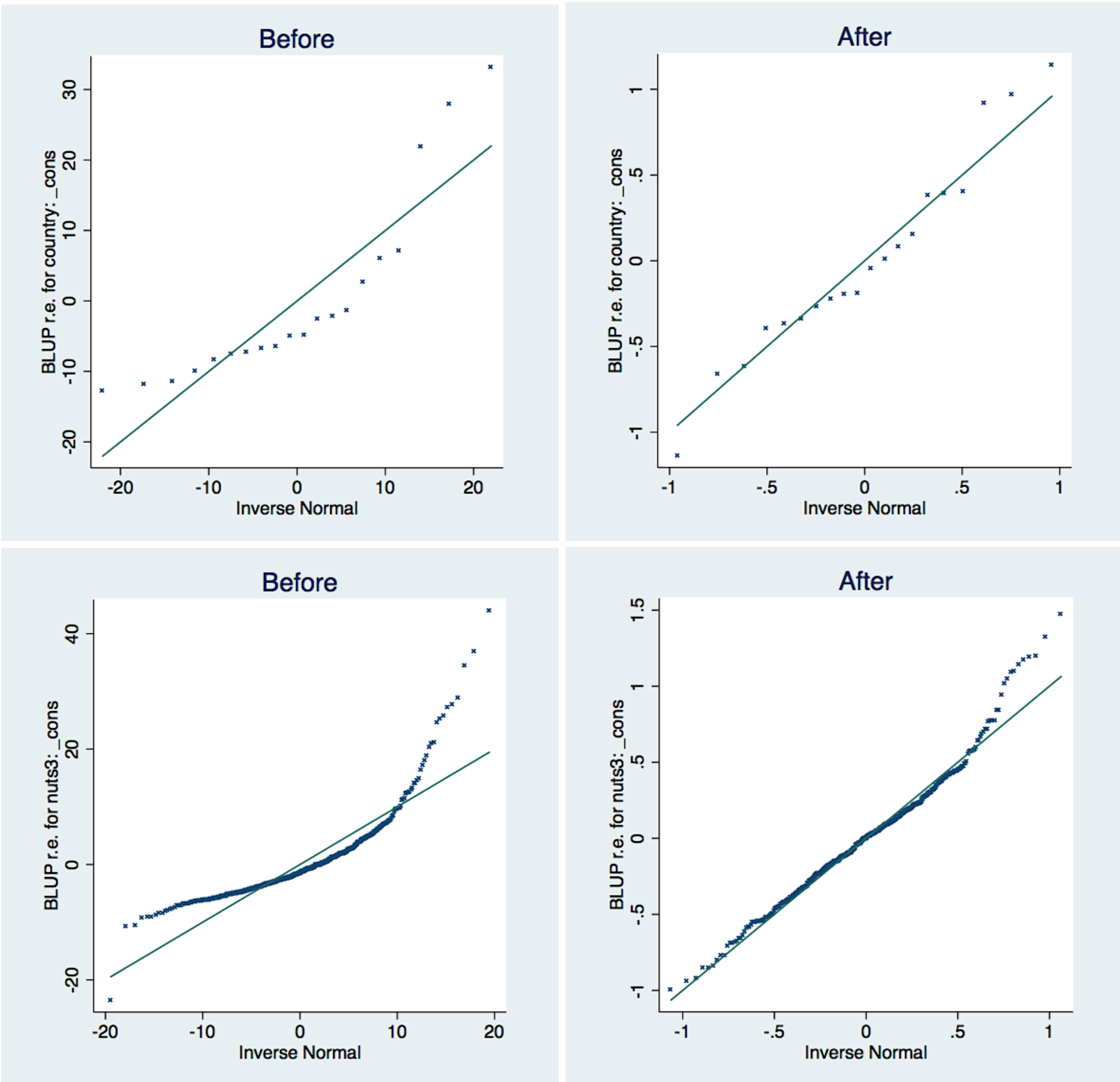
The second component includes the fixed effects part of the ML model and the interpretation is similar to that of an OLS regression. In this base model, the fixed part only includes the intercept. Later in the paper when more variables will be added, their coefficients will be presented in this fixed part of the ML model. Because this model is an intercept only model, the value of 22.63 represents the mean PT use percentage, meaning on average, PT accounts for 22.63% of the modal split in the 680 European cities. This mean is also statistically significant at the 0.05 level as represented in the 95% confidence interval not crossing zero, thus the mean is significantly different from zero.

The final component of this output provides the random effects part of the model. This would include the various variance components of the different levels and the within level variance, here the Variance Partition Coefficient (VPC) is displayed. Below this table is an output of the LR test. This test signifies that whether the ML model is better than a single-level model model in describing the data. With the p-value zero, the null hypothesis that a single level model describes the model better is rejected, thus the ML model can continue to be built upon. Before going into further detail of the variances, such as the Variance Partition Coefficients (VPCs) and the Intraclass Correlation Coefficients (ICCs), the residuals must be checked for normality.

Quantile-quantile (QQ) plots are produced to examine whether the NUTS3 and country level effect residuals are approximately normally distributed. Normality is important for inference reasons, as biased residuals would lead to an incorrect interpretation of the statistical output. This is usually problematic for models with smaller samples, but nonetheless it is still useful to check. As the residuals seem somewhat abnormal from the QQ plots, a method to counteract this is to logarithmically transform the dependent variable *ptuse*, converting this level-level model into a log-level model. Thus, taking the natural logarithm of PT use creates the variable *logptuse* making this a log-level model. The QQ plots are plotted again with the outcomes in *Figure 10*, showing the before and after distribution of the residuals. Observing the distribution of the residuals in *Figure 10*, it seems that log transforming the dependent variable has fixed the somewhat right skewed residuals.

Figure 10

QQ plots of the country and NUTS3 effects residuals (before and after)



Now that the model uses *logptuse*, it helps the residuals look more normal. The model must be run again through Stata to see if there are any changes to the estimates. The new output using *logptuse* as the dependent variable is presented in *Figure 11*.

Figure 11

New base model output of *–xtmixed logptuse || country: || nuts3:, mle– variance–*

Group Variables	No. of Groups		
Country	20	No. of observations:	680
NUTS3	476	Log likelihood:	-515.49569

Variables	Coefficient	95% Confidence Interval	
intercept	2.791932*	2.499396	3.084468

Level Effects	Estimate	VPC	95% Confidence Interval	
Country	0.3866722*	55.73%	0.1821673	0.8207587
NUTS3	0.2017241*	29.07%	0.1673493	0.2431598
City	0.1054605*	15.20%	0.0885185	0.1256452

LR test vs. linear regression:	chi2(2)=409.69	Prob > chi2 = 0.0000

*Statistically significant at the 0.05 level

Compared to *Figure 9*, *Figure 11* shows that the coefficient for the intercept has changed. For the intercept and the ML variances, the estimates have decreased dramatically, which can be explained by the logarithmic transformation. The most major change is the way of interpreting the coefficients. For example, before the intercept was the mean PT percentage of the modal split, now the intercept is the mean logarithm of the percentage of PT use. Because the mean logarithm of the percentage of PT use does not provide much intuitive interpretation, there must be a reverse log calculation of the log transformation to interpret the effect of coefficients on the dependent variable. To interpret the intercept, the coefficient of 2.79 must be exponentially transformed to give a value of 16.31, which is the mean of PT use. When dependent variable will be added on later in the process, the effect they will have on PT use is a factor of $e^{coefficient}$, which this factor must multiply the expected PT use.

Now that the model has been corrected for its abnormal residuals, the variances are investigated further by calculating the VPCs and ICCs. The VPC indicates how much variance a certain level explains and the ICC indicates how correlated the observations are within a cluster.

As such the city level VPCs is:

$$VPC_e = \frac{\sigma_e^2}{\sigma_w^2 + \sigma_v^2 + \sigma_e^2} = \frac{0.1054605}{0.3866722 + 0.2017241 + 0.1054605} = 15.19\%$$

As such the NUTS3 level VPCs is:

$$VPC_v = \frac{\sigma_v^2}{\sigma_w^2 + \sigma_v^2 + \sigma_e^2} = \frac{0.2017241}{0.3866722 + 0.2017241 + 0.1054605} = 29.07\%$$

As such the Country level VPCs is:

$$VPC_w = \frac{\sigma_w^2}{\sigma_w^2 + \sigma_v^2 + \sigma_e^2} = \frac{0.3866722}{0.3866722 + 0.2017241 + 0.1054605} = 55.72\%$$

This result of VPC_e = 15.19% indicates that 15.19% of the variation in PT use is explained on the city level. The NUTS3 level and the country level explain 29.07% and 55.72% of the variance respectively. It is interesting to find that the country level explains more than half of the variance already. Tracking the variance estimates from this point is important because it will provide insight on how the composition effect evolves throughout the model building process.

The concept behind the ICC measure is that it calculates the correlation between two observations within the same level, but different groups in the lower level. For example, the country level ICC would indicate how two observations are correlated within the same country, but in different NUTS3 regions.

As such, the country level ICC is as follows:

$$ICC_w = \frac{\sigma_w^2}{\sigma_w^2 + \sigma_v^2 + \sigma_e^2} = \frac{0.3866722}{0.3866722 + 0.2017241 + 0.1054605} = 55.72\%$$

The ICC for the NUTS3 level:

$$ICC_{wv} = \frac{\sigma_w^2 + \sigma_v^2}{\sigma_w^2 + \sigma_v^2 + \sigma_e^2} = \frac{0.3866722 + 0.2017241}{0.3866722 + 0.2017241 + 0.1054605} = 84.80\%$$

The country level ICC puts out the same result as the country level VPC. This is because this model does not include any random slope variables, resulting in the same ICC and VPC for the country level. As the ICC measure is calculated for the lower levels, the correlation within the level increases, meaning that, cities from the same country, or even the same NUTS3 region, do not have comparable levels of PT use in their modal split. Overall, there seems to be a rather moderate degree of clustering already in the data with the country level almost explaining half of the variation. It would be interesting to see how the model changes with the inclusion of explanatory variables. Because the VPC measure is a relative measure, it will not indicate how much absolute level variance is has been captured by the model. Thus, to properly track the level effects, it is important to not the progression of the estimate, rather than the VPC.

Now that the model has been fitted, Stata can predict the different level residuals to make predicted effects of the national and NUTS3 levels. In *Figure 12*, each level is ordered by the predicted magnitude of their effects from highest to lowest, showing the results of the top 3 observations of each level. This table summarizes the overall level effects, such as Czech Republic has the largest predicted country effect and the eastern part of inner London has the largest NUTS3 effect.

Just as the top 3 NUTS3 regions and countries with the highest net level effects have been identified in *Figure 11*, the same can be done to the top 3 NUTS3 regions and countries with the lowest net level effects. These are presented in *Figure 13*. One interesting speculation is that the highest city and NUTS3 region effects seem to be coming from large metropolitan areas. The highest country effect does not have an obvious explanation can could be researched further. Similarly, the lowest predicted effects seem to come from smaller cities or NUTS3 regions with less large cities in Europe. Perhaps the countries reflect the overall consistency of its cities and NUTS3 regions. For example, the Netherlands has large global cities such as Amsterdam and Rotterdam, but perhaps with the presence of a lot of smaller cities, the overall country effect of the Netherlands is quite small.

Figure 12

Rank of the top 3 NUTS3 regions and countries by the highest net predicted effects

Rank	NUTS3 Region	Country
1	Inner London (East), UK	Czech Republic
2	Inner London (West), UK	Slovakia
3	Val-d'Oise, France	Switzerland

Figure 13

Rank of the top 3 NUTS3 regions and countries by the lowest net predicted effects

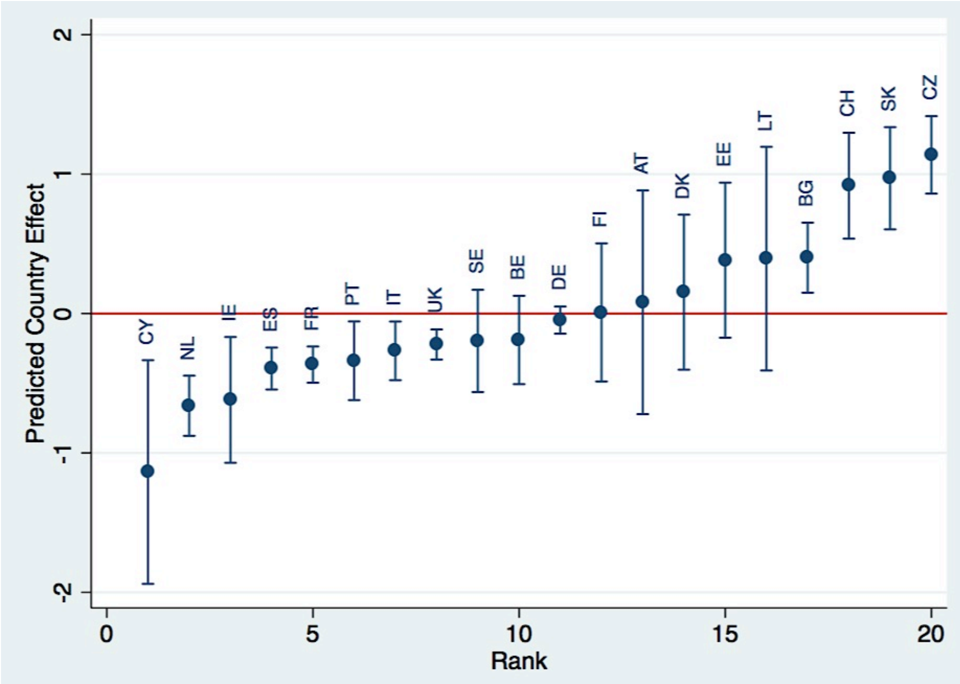
Rank	NUTS3 Region	Country
1	Västerboteens län, Sweden	Cyprus
2	Tâmega, Portugal	Ireland
3	Kempten, Kreisfreie Stadt, Germany	The Netherlands

The different net level effects can be visually represented with the use of caterpillar plots. With these plots' magnitudes and observations that deviate from the average can be analyzed. The net country effects are analyzed first in *Figure 14*.

Each country's confidence interval in the predicted net country effect differs from one another in *Figure 14*. This is due to an unbalanced data as not all countries had the same amount of observations, such as France, Germany, Spain, and the UK had relatively more observations than countries such as Austria, Cyprus, and Lithuania. The red line going through the caterpillar plot indicated the average country. In combination of the red line and the confidence intervals of each country, it is possible to distinguish how many countries statistically differ from the average. On the country level, Cyprus, France, Ireland, Italy, Netherlands, Portugal, Spain, and the UK have PT use, which is significantly lower than the average. On the other hand, Bulgaria, Czech Republic, Slovakia, Switzerland have significantly higher than average PT use.

This approach can be done on the NUTS3 level, but unfortunately a caterpillar plot would be rather unhelpful due to the sheer number of NUTS3 regions. Nonetheless, the regions that differ form the average can be counted, with 71 out of 476 NUTS3 regions significantly differ from the average. This is a rather small proportion of the sample, meaning that the PT use is very similar when comparing region to region.

Figure 14
Caterpillar plot of the net country effect



The interpretations made from the base model should be taken with care, as this is an intercept only model. An intercept only model does not control for any variables that may influence the PT use. Thus the composition effect may be large in this model, making it difficult to construct contextual inferences. The purpose of these results is to establish a baseline, so that changes in the level effects can be tracked. If by the end of the research, more or less the same countries remain on the top and bottom rank, perhaps the composition effect was not as large to begin with as not much has changed.

5.2 Adding Explanatory Variables

With the base model thoroughly established, the next step in building the ML model is to add explanatory variables. As the analytical approach is more familiar now, building up the model will continue at a faster pace, with a full analysis of the final model only.

The procedure for optimizing the ML model is to add independent variables and LR testing it against a restricted model, which should be nested within the current model. Step by step, this is done until the LR test rejects a new model, as it would not provide any further explaining power. This method comes with a set back because of the unbalanced data. As each variable has its own set of cities, not all variables have observations from the same cities. Thus, introducing new variables into the model increases the probability of the most recent model being rejected. Therefore, there is an expectation that at one point, there will not be enough observations to sufficiently provide a decent amount of explanation power to improve the model. At this point, the model would be at its optimum.

Keeping in mind the base model in chapter *5.1*, model 1 will include all the level one variables: *student, ptcost, carownership, commutetime,* and *age65p*. A description of all the variables can be found in *Appendix 1*. The output for model 1 is in *Figure 15*.

Figure 15
Stata output of model 1: *xtmixed logptuse student ptcost carownership commutetime age65p || country: || nuts3:, mle variance*

Group Variables	No. of Groups		
Country	9	No. of observations:	112
NUTS3	108	Log likelihood:	-63.823586

Variables	Coefficient	Factor	95% Confidence Interval	
intercept	2.7513*		1.796659	3.705941
student	0.1828068	1.20	-0.9613744	1.326988
ptcost	0.0100058*	1.01*	0.0021593	0.0178524
carownership	-0.0012654*	1.00*	-0.0024301	-0.0001007
commutetime	0.0490426*	1.05*	0.0319605	0.0661247
age65p	-0.0360649*	0.96*	-0.0721163	-0.0000136

Level Effects	Estimate	VPC	95% Confidence Interval	
Country	0.287867*	65.14%	0.096831	0.8557945
NUTS3	0.1155735*	26.15%	0.0616093	0.2168053
City	0.0384552*	8.70%	0.0085368	0.1732273

*Statistically significant at the 0.05 level

Because this is a log-level model, a “Factor” column has been created to represent the impact of the explanatory variables on the dependent variable. This

“Factor” is the exponential transformation of the coefficient. The interpretations would be as follows. Normally in a level-level model, the intercept would signify the mean PT use in the sample. Reverse transforming the intercept would give a mean of 15.66. This would mean that in model 1, the average PT use across 108 cities is 15.66 percent. This mean is statistically significant to the 0.05 level. The variables *ptcost, carownership, commutetime,* and *age* are also statistically significant. An increase in these variables by one unit would increase PT use by the product of the factor value when keeping all else equal (Benoit, 2011). As a result, any factor that is below 1 would mean the variable has a negative association with the dependent variable. Therefore, *ptuse*, *carownership*, and *commutetime* all have a positive association with PT use, where as *age65p* has a negative association.

Other observations include the level effects, which are all significant at the 0.05 level. When comparing to the intercept only model, the variances have decreased on all levels. Meaning that the inclusion of the variables *student, ptcost, carownership, commutetime,* and *age* in model 1 has captured some of the country, NUTS3, and city effects. This suggests that by controlling for these variables, a lot of the within level variation can be explained by model 1. Furthermore, countries and NUTS3 regions have different effects on cities with a large share of PT use verses cities with a low share of PT use.

As mentioned earlier in the paper, the number of observations is expected decreased. This is evident in model 1, where the number of observations has decreased from 680 in the base model to 108. This would be a reoccurring problem that will cause problems when running the LR test, as it will be comparing two models with different observations. This is easily fixed with Stata’s –e(sample) – option, which uses the sample of the previous model. This will be the persistent limitation in building the model where not all cities have a measurement for a certain variable. With a p-value of 0.0000 attained from the LR test, the added variable significantly improves the model compared to the base model. Deeper interpretations will be refrained since this is the model building process and the model could still have a large composition effect, making it difficult to make interpretations on the contextual effect of the model.

As model 1 was successful, model 2 will include the addition of NUTS3 control variables. The output of model 2 is presented in *Figure 16*.

Figure 16

Stata output of model 2: *xtmixed logptuse student ptcost carownership commutetime age65p area popden gdppc landuse|| country: || nuts3:, mle variance*

Group Variables	No. of Groups			
Country	7		No. of observations:	52
NUTS3	48		Log likelihood:	-19.831722

Variables	Coefficient	Factor	95% Confidence Interval	
intercept	2.609082*		1.677233	3.54093
student	0.8604434	2.36	-0.6337402	2.354627
ptcost	0.0019577	1.00	-0.0120575	0.015973
carownership	-0.0008482*	1.00*	-0.0016789	-0.0000175
commutetime	0.0471269*	1.05*	0.0299435	0.0643102
age65p	0.0321047	1.03	-0.0312688	0.0954782
popden	0.000584*	1.00*	0.0002226	0.0009455
gdppc	-0.0000363*	1.00*	-0.0000567	-0.0000159
area	-0.0000274*	1.00*	-0.0000427	-0.000012
landuse	-1.374889	0.25	-4.269738	1.51996

Level Effects	Estimate	VPC	95% Confidence Interval	
Country	5.58E-22	5.58E-20%	.	.
NUTS3	0.0975167*	72.75%	0.0415721	0.2287472
City	0.0365198*	27.25%	0.0070393	0.1894633

*Statistically significant at the 0.05 level

Most of the newly added variables are significant at the 0.05 level. This includes variables *popden, gdppc,* and *area*. These variables all have a factor of 1, due to rounding. If investigating the factors of the variables *popden, gdppc,* and *area* deeper, then *popden* is slightly larger than 1, meaning it increases PT use. Variables *gdppc* and *area* have a slight smaller value than one, thus decreasing PT use. Because this logarithmic transformation is a scalar transformation, only the magnitudes of the coefficients change. The sign of the coefficients should remain the same. These associations seem to be consistent with the literature findings, where population density is positively associated with PT use and income has a negative association, keeping all else equal. Compared to model 1, model 2 has a decreased mean of 13.59. This could mean that the composition effect is decreasing, as the model is slowly reaching its “true” mean.

The level effects have some irregularity in the sense that Stata did not give a 95% confidence interval for the country effect. This model seems to have converged correctly with no signs of errors. To stay prudent, the assumption is that the country effect is insignificant. The NUTS3 and city effect are significant at the 0.05 level and it seems that the NUTS3 variance decreased more than the city variance when comparing to model 1. This would mean this model is capturing more of the NUTS3 effect. Conducting the LR test confirms that this model adds value with a P-value of 0.0002.

The next step would be to add the policy dummy variable. Unfortunately, Stata omitted the policy dummy variables due to multicollinearity. Accordingly, the output of this model is the same as model 2. This would mean Hypothesis 3 is not confirmed, which is quite a shame because the more interesting *policy* variable would have been very exciting to test as it would demonstration the effects of the three different types of policies. Interaction effects have also been tested with the *student* variable. There were no significant interactions that passed the LR test, thus it was not pursued any further. As a result, model 2 is thus far the most optimal.

5.3 Final Model

Model 3 is created to investigate whether there is heterogeneity of the dependent variables across the NUTS3 level. The final result is that the LR test only approved a random slope of the variable *ptcost* with a P-value of 0.0109. Other variables failed the LR test when allowing for heterogeneity on the NUTS3 and country level. Because no more additional things can be added to improve model 3, it is the final model of this research paper. This means that Hypothesis 2a and 2b could not be confirmed, as the model did not converge when allowing the *student* variable to have a random slope. Model 3 is presented in *Figure 17*.

Figure 17

Model 3 output of –*xtmixed logptuse student ptcost carownership commutetime age65p popden gdppc area landuse|| country: || nuts3: ptcost, covariance (unstructured) mle variance*–

Group Variables	No. of Groups		
Country	7	No. of observations:	52
NUTS3	48	Log likelihood:	-15.309479

Variables	Coefficient	Factor	95% Confidence Interval	
intercept	2.396376*		1.58139	3.211361
student	1.149266*	3.16*	0.0757966	2.222736
ptcost	-0.0005362	1.00	-0.0146593	0.0135869
carownership	-0.0003342	1.00	-0.0010692	0.0004007
commutetime	0.0420692*	1.04*	0.0251609	0.0589776
age65p	0.0320402	1.03	-0.0177341	0.0818145
popden	0.0004818*	1.00*	0.0001855	0.000778
gdppc	-0.0000344*	1.00*	-0.0000582	-0.0000107
area	-0.0000262*	1.00*	-0.0000458	-6.46E-06
landuse	0.1321226	1.14	-2.517989	2.782234

Level Effects	Estimate	VPC	95% Confidence Interval	
Country	1.25E-15			
NUTS3	0.1923727*	77.69%	0.0561429	0.6591612
City	0.0547606*	22.11%	0.0258517	0.1159973

Random Slop	Estimate	VPC	95% Confidence Interval	
NUTS3				
ptcost	0.0004964*	0.20%	0.0001745	0.0014124
cov(ptcost,_cons)	-0.0097725		-0.0204602	0.0009151

*Statistically significant at the 0.05 level

When allowing for a random slope in *ptcost*, the mean PT use decreases to 10.98. Furthermore, variables *student, commutetime, popden, gdppc* and *area* have statistically significant associations at the 0.05 level. More specifically, an increase in commute time and population density would lead to an increase in PT use *ceteris paribus*. This relationship is rather intuitive, as PT would probably become more convenient than the alternative when knowing the commute time would be long. Population density is popularly supported by scientific literature for having a positive association with PT use, which this research can confirm with this final model. Income and area also have unsurprising results as the tendency of increased income is associated with less PT use, whereas the larger an area would be, one can imagine that it would be more costly to develop and sustain a competitive PT system. The most remarkable result is that the *student* variable has a positive effect of a factor 3.16. Although it has been supported by scientific literature previously, it was not expected to have such a significant effect. This would mean that Hypothesis 1 is confirmed, that an increasing share of students does have a positive effect on the share of PT use. This effect is the largest effect seen in this research and could be due to omitted variable bias, leading to an over estimation of the *student* coefficient. The level effects are similar to that of model 2 in that there is a significant NUTS3 and city level effect on the 0.05 level.

This research seems to have predominately captured the country effect in the model. This country effect is investigated further by ranking the highest and lowest predicted country effect. This is done in the same manner as in chapter 5.1. The results are presented in *Figure18*. When comparing the ranking in *Figure 18* and *Figure 12*, it is interesting to see that the Czech Republic and Slovakia are still in the first and second places in terms of the country effect. Perhaps this is coincidence or possibly that the composition effect for these two countries were low to begin with. Seeing that the lowest country effects from *Figure 18* and *Figure 13* differ may suggest that this composition effect is less strong for countries with a high country effect, although this is a bold assumption to make.

Figure 18

Rank of the top 3 NUTS3 regions and countries by the highest net predicted effects

Rank	Highest Country Effect	Lowest Country Effect
1	Czech Republic	Estonia
2	Slovakia	Spain
3	Lithuania	Sweden

To summarize the development of the model, a visual representation is made where each model is compiled together in *Figure 19*. From *Figure 19,* contains the 3 models that were confirmed by the LR test in this paper. As expected and mentioned earlier, the number of observations decreased as the model developed. This research seems to have predominately explained the differences a country may have on a city. The NUTS3 region and city effect still seem to affecting the data, but to of a lesser extent when compared to models 1 and 2. When looking at *carownership* in models 2 and 3, this variable become insignificant when allowing for heterogeneity in the PT cost effect. As the two models are essentially the same, it may suggest that car ownership and PT cost may be capturing an income effect. This could be further supported by the fact that *ptcost* changes direction in the effect from model 2 to model 3. When assuming *ptcost* has a fixed effect on the model, it gives a somewhat unintuitive interpretation of an increase in PT cost increases PT use. This also may point to an increasing wage within the city, thus as the cost rise it does not have a detrimental effect on PT use. Once allowing this PT cost effect to be random, it could be capturing the effect better, and thus *carownership* becomes insignificant.

Figure 19
Summary of the models

	Base Model	**Model 1**	**Model 2**	**Model 3**
Number of observations	680	112	52	52
Mean	16.31*	15.66*	13.59*	10.98*
student	.	+	+	+*
ptcost	.	+*	+	–
carownership	.	–*	–*	–
commutetime	.	+*	+*	+*
age65p	.	–*	+	+
popden	.	.	+*	+*
gdppc	.	.	–*	–*
area	.	.	–*	–*
landuse	.	.	–	+
Level Effects				
Country	0.3866722*	0.287867*	5.58E-22	1.25E-15
NUTS3	0.2017241*	0.1155735*	0.0975167*	0.1923727*
City	0.1054605*	0.0384552*	0.0365198*	0.0547606*
Random Slope				
ptcost	.	.	.	0.0004964*
cov(ptcost,_cons)	.	.	.	-0.0097725

*Statistically significant at the 0.05 level

Because ML models use maximum likelihood estimations, results may differ when rerunning the model. This could be a sign of multicollinearity. In this study, this problem seems to be rather severe when running model 3 when including a random slope for *ptcost*. Rarely, Stata had to be closed and opened again for the model to run properly. Occasionally, the acceptance of a random slope by the LR test seems to alternate between *ptcost* and *carownership*, which may suggest that there is also heterogeneity in the effect of car ownership. Having said that, the direction of the effect seems to be stable when running model 3.

Chapter 6: Conclusion

This research paper builds an ML model with the intentions of finding the effect of students on PT use within European cities. There are a few noteworthy outcomes that have very interesting implications. Not only is it confirmed Hypothesis 1 that the students share has a positive effect on PT share, but also that it has the most dominant effect compared to other factors such as commuting time, population density, income, and area. This could mean that PT service providers should focus more on the student population within a city to increase usage. Furthermore, it seems that the regional effect is stronger than the country effect on PT use. This sheds light on an interesting aspect of PT that perhaps cities did not consider before, as a broader regional effect may influence a city's PT use more than the country. Thus, when making policy decisions about a cities transport system, not only within city factors like students should be considered, but also external factors, such as its surrounding region. Although Hypothesis 2a and 2b were not confirmed, heterogeneity was found in the effect of PT cost. This would mean each NUTS3 regions has a different PT cost effect on the share of PT use.

This study has intentionally focused on the European level because it would be difficult to extend the validity of the results to a broader scale. Even within western cultures such as the US there are still large differences in travel behavior when compared to Europe. These differences are not limited to cultural differences but also social, political, and economic differences, thus the conclusions made in this study are strictly based on European data.

A number of limitations were encountered. The largest limitation is the unbalanced data used in this research. Although there could be many observations for a certain variable, if the sample of those observations is different from one variable to another, it makes it difficult to compile a set of cities that have all the different variables measured. This was largely the case in this study, to the point where some variables such as *commutedist* and *rain* had to be dropped, merely because they would exclude too many cities from the analysis. This unbalanced data also has an impact on optimizing the model. The addition of a new variable decreases the number of observations within the model, eventually reaching a limit where adding another variable can be highly detrimental to the model. If all cities had measurements for all the variables, perhaps this analysis could have gone deeper into the *policy* variable and try to confirm Hypothesis 3, including interaction effects within the model. The models that are run could also be suffering from omitted variable bias, as seen with a relatively high coefficient for *student*. Fixing this problem would be difficult to solve, as complete datasets would be needed. Finally, there are signs of multicollinearity in the model building process. Although correlations were no higher than 0.70, as seen in *Figure 8*, the model seems to suffer from multicollinearity, evidenced in the instability of model 3.

These limitations should encourage countries and their respective statistical offices to consistently and systematically collect data on a regular basis. This would provide sufficient data to scholars and would allow them to provide a better analysis in their research. Perhaps even rerunning the same research with better data may change the initial conclusions made.

For future research, it would be interesting to see how a discount policy for students influences the PT use, as this study was not able to incorporate it. Additionally, this study uses a ML model, which has a strict exogeneity assumption in the explanatory variables. This assumption may be difficult to hold in real life, as there could be influences between the variables. Hence, it would be interesting to run a similar model using Structural Equation Modeling (SEM), where theses exogeneity assumptions may be relaxed.

References

Bagley, M. N. and Mokhtarian, P. L., 2002. The Impact of Residential Neighborhood Type on Travel Behavior: A Structural Equation Modeling Approach. *Annals of Regional Science*, 36(2), 279-297.

Balcombe, R., Mackett, R., Paulley, N., Preston, J., Shires, J., Titheridge, H., Wardman, M., White, and P., 2004. The Demand for Public Transport: A Practical Guide. *TRL Report*. 593, 1-237

Brown, J., Hess, D.B., and Shoup, D. 2003. Fare-Free Public Transit at Universities. *Journal of Planning Education and Research.* 23, 69-82.

Brown, J., Hess, D.B., and Shoup, D., 2001. Unlimited Access. *Transportation.* 28(3), 233-267.

Buehler, R., 2011. Determinants of Transport Mode Choice: A Comparison of Germany and the USA. *Journal of Transport Geography.* 19, 644-657.

Cervero, R., 2002. Build Environments and Mode Choice: Toward a Normative Framework. *Transportation Research Part D.* 7, 265-284.

Chen, X., Liu, X., and Li, F., 2013. Comparative Study on Mode Split Discrete Choice Models. *Journal of Modern Transport.* 21(4), 266-272.

Dargay, J., Hanly, M., 2007. Volatility of Car Ownership, Commuting Mode and Time in the UK. *Transportation Research Part A*. 41 (10), 934–948.

Frank, L.D., 1994. An Analysis of Relationships Between Urban Form (Density, Mix, and Jobs: Housing Balance) and Travel Behavior (Mode Choice, Trip Generation, Trip Length, and Travel Time). *Washington State Department of Transportation.* Report number: WA-RD 351.2, 1-284.

Frank, L.D., and Pivo, G., 1994. Impact of Mixed Use and Density on Utilization of Three Modes of Travel: Single-Occupant Vehicles, Transit, and Walking. *Transportation Research Record,* 1466, 44-52.

Friedmann, J., 1986. The World City Hypothesis. *Development and Change*, 17: 69-83.

Hill, R.C., and Kim, J.W., 2000. Global Cities and Developmental States: New York, Tokyo and Seoul. *Urban Studies*, 37(12), 2167-2195.

Kenworthy, J., and Laube, F.B., 1999. Pattern of Automobile Dependence in Cities: An International Overview of Key Physical and Economic Dimensions with Some Implications for Urban Policy. *Transportation Research Part A.* 33, 691-723.

Kim, S., Ulfarsson, G.F., 2008. Curbing Automobile Use for Sustainable Transportation: Analysis of Mode Choice on Short Home-Based Trips. *Transportation*, 35(6), 723–737.

Kitamura, R., 2009. A Dynamic Model System of Household Car Ownership, Trip Generation, and Modal Split: Model Development and Simulation Experiment. *Transportation*. 36(6), 711–732.

Kitamura, R., Mokhtarian, P. L., and Laidet, L., 1997. A Micro-Analysis of Land Use and Travel in Five Neighborhoods in the San Francisco Bay Area. *Transportation*, 24(2), 125-158.

Leckie, G., 2013. Three-Level Multilevel Models – Stata Practical. LEMMA VLE Module 11, 1-52. http://www.bristol.ac.uk/cmm/learning/course.html

Litman, T., 2005. Land Use Impacts on Transport: How Land Use Factors Affect Travel Behavior. *Victoria Transport Policy Institute.* 1-43.

Litman, T., 2004. Transit Price Elasticities and Cross-Elasticities. *Journal of Public Transportation*, 7(2), 37-58.

Newman, R., Dellinger, A., Anderson, M., Bonomi, A., Rivara, F., and Thompson, R., 2009. Preferred Modes of Travel Among Older Adults: What Factors Affect the Choice to Walk Instead of Drive?. *Journal of Safety Research.* 40(5), 395–398.

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., Shires, J., and White, P., 2006. The Demand for Public Transport: The Effects of Fares, Quality of Service, Income and Car Ownership. *Transport Policy.* 13(4), 295–306.

Pinjari, A.R., Pendyala, R.M., Bhat, C.R., and Waddell, P.A., 2007. Modeling Residential Sorting Effects to Understand the Impact of the Built Environment on Commute Mode Choice. *Transportation*. 34(5), 557–573.

Rodríguez, D.A., and Joo, J., 2004. The Relationship between Non-Moterized Mode Choice and the Local Physical Environment. *Transport Research Part C.* 9, 151-173.

Sabir, M., 2011. Weather and Travel Behaviour. *Vrije Universiteit Amsterdam*. 1-138.

Santos, G., Maoh, H., Potoglou, D., von Brunn, T., 2013. Factors Influencing Modal Split of Commuting Journeys in Medium-Size European Cities. *Journal of Transport Geography*. 30, 127-137.

Scheiner, J., 2010. Interrelations between Travel Mode Choice and Trip Distance: Trends in Germany 1976–2002. *Journal of Transport Geography.* 18(1), 75–84.

Schwanen, T., 2002. Urban Form and Commuting Behaviour: A Cross-European Perspective. *Tijdschrift voor Economische en Sociale Geografie*, 93(3), 336–343.

Shannon, T., Giles-Corti, B., Pikora, T., Bulsara, M., Shilton, T., and Bull, F., 2006. Active Commuting in a University Setting: Assessing Commuting Habits and Potential for Modal Change. *Transport Policy*, 13, 240-253.

Sumalee, A., Uchida, K., Lam, W.H.K., 2011. Stochastic Multi-Modal Transport Network Under Demand Uncertainties and Adverse Weather Condition. *Transportation Research Part C*, 19(2), 338–350.

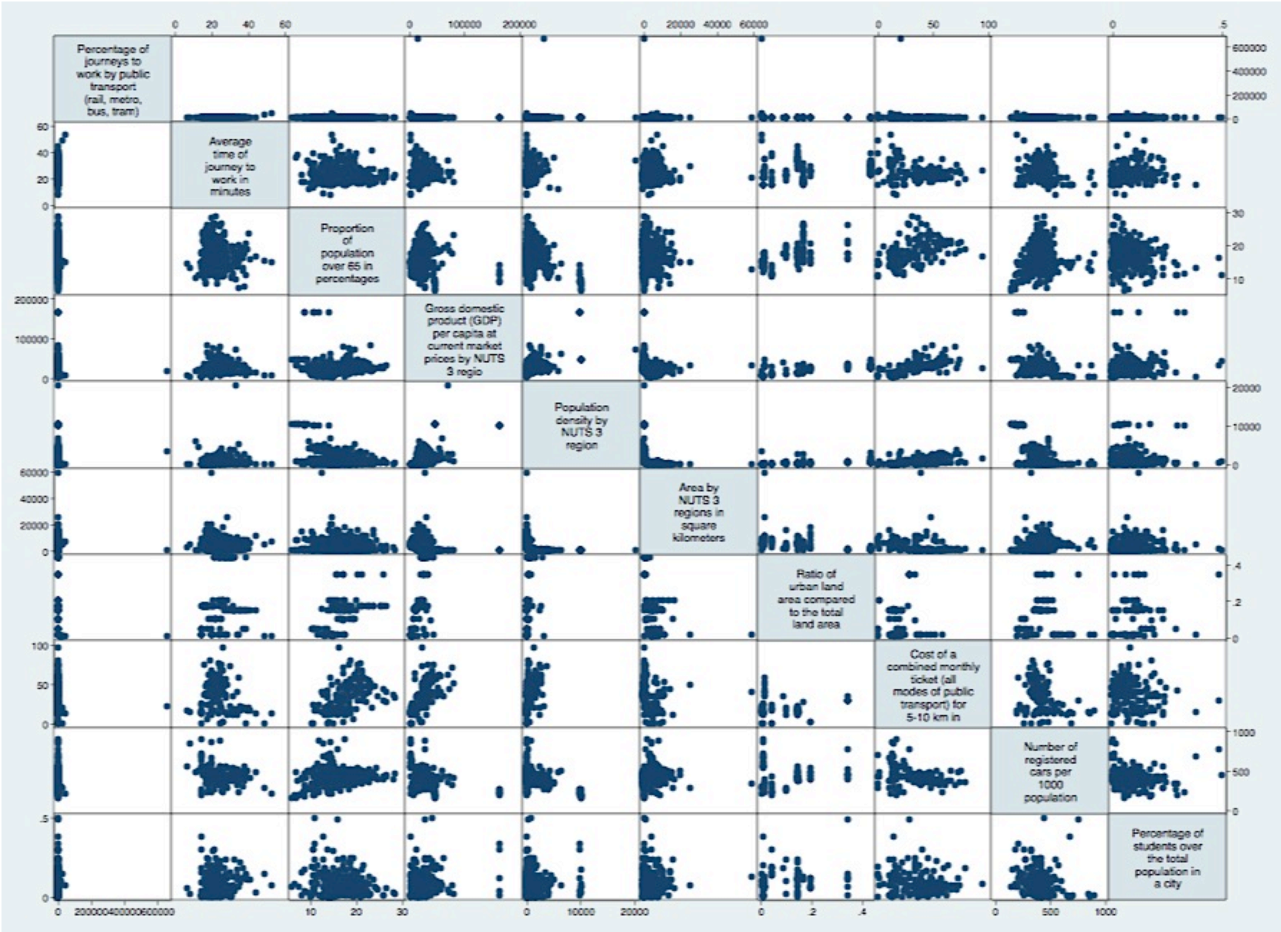
Susilo, Y., Maat, E., 2007. The Influence of Built Environment to the Trends in Commuting Journeys in the Netherlands. *Transportation*. 34(5), 589–609.

Van Acker, V., Witlox, F., and Van Wee, B., 2007. The Effects of the Land Use System on Travel Behavior: A Structural Equation Modeling Approach. *Transportation Planning and Technology*. 30(4), 331-353.

Zhang, M., 2004. The Role of Land Use in Travel Mode Choice: Evidence from Boston and Hong Kong. *Journal of the American Planning Association*. 70(3), 344-360.

Appendix

1. Graph matrix of possible outliers



2. General description of the data

```
Contains data from Final.dta
  obs:           680
 vars:            25                          2 Aug 2015 22:39
 size:       174,080
-------------------------------------------------------------------------------------------
              storage  display    value
variable name   type   format     label      variable label
-------------------------------------------------------------------------------------------
city            int    %10.0g                City ID
nuts3           int    %10.0g                NUTS 3 ID
country         byte   %10.0g                Country ID
nationcode      str14  %14s                  Nation code
nuts3code       str14  %14s                  NUTS3 Code
citycode        str14  %14s                  City code
year            int    %10.0g                Years 1990-2014
cityname        str42  %42s                  City Name
ptuse           double %10.0g                Percentage of journeys to work by public
                                               transport (rail, metro, bus, tram)
student         float  %9.0g                 Percentage of students over the total
                                               population in a city
ptcost          double %10.0g                Cost of a combined monthly ticket (all
                                               modes of public transport) for 5-10 km
                                               in
carownership    double %10.0g                Number of registered cars per 1000
                                               population
rain            double %10.0g                Rainfall in litre/m2
commutetime     double %10.0g                Average time of journey to work in minutes
commutedist     double %10.0g                Average length of journey to work by
                                               private car in km
age65p          float  %9.0g                 Proportion of population over 65 in
                                               percentages
NUTS32010code~e str78  %78s                  NUTS 3 2010 code and name
gdppc           long   %10.0g                Gross domestic product (GDP) per capita at
                                               current market prices by NUTS 3 regio
popden          double %10.0g                Population density by NUTS 3 region
area            double %10.0g                Area by NUTS 3 regions in square
                                               kilometers
landuse         float  %9.0g                 Ratio of urban land area compared to the
                                               total land area
policy          float  %16.0g     policy     group(Free Discount None)
fulldisc        byte   %8.0g                 policy==Full discount
partdisc        byte   %8.0g                 policy==Partial Discount
nodisc          byte   %8.0g                 policy==No Discount
-------------------------------------------------------------------------------------------
```

3. Summary of the data

Variable	Obs	Mean	Std. Dev.	Min	Max
city	680	448.2162	304.4726	2	976
nuts3	680	736.5074	387.6203	1	1357
country	680	16.86471	10.22253	1	32
nationcode	0				
nuts3code	0				
citycode	0				
year	680	2007.932	4.05574	1990	2012
cityname	0				
ptuse	680	19.36876	14.89386	2	99
student	305	.0850219	.0771628	0	.4981493
ptcost	178	36.01264	18.61247	0	95
carownership	413	421.3341	96.0794	146.5	898.4
rain	138	733.821	254.2532	137.4	1968.4
commutetime	410	23.38232	5.73134	7	44
commutedist	225	14.97502	5.032618	2	32
age65p	498	16.56044	3.903646	6.1	28.5
NUTS32010c~e	0				
gdppc	612	26601.47	17193.24	2600	164100
popden	658	1089.838	1885.353	4.7	20893.4
area	659	3535.009	4370.569	13.4	59284
landuse	132	.2008364	.1524954	.0113456	.4349966
policy	680	2.185294	.501328	1	3
fulldisc	680	.05	.2181054	0	1
partdisc	680	.7147059	.4518868	0	1
nodisc	680	.2352941	.4244947	0	1

4. Codebook of the different levels

```
city                                                                 City ID

              type:  numeric (int)

             range:  [2,976]                      units:  1
     unique values:  680                      missing .:  0/680

              mean:   448.216
         std. dev:    304.473

       percentiles:        10%       25%       50%       75%       90%
                          82.5     184.5     379.5     769.5     905.5
```

```
nuts3                                                              NUTS 3 ID

              type:  numeric (int)

             range:  [1,1357]                     units:  1
     unique values:  476                      missing .:  0/680

              mean:   736.507
         std. dev:     387.62

       percentiles:        10%       25%       50%       75%       90%
                         142.5     474.5       663    1177.5      1247
```

```
country                                                           Country ID

              type:  numeric (byte)

             range:  [1,32]                       units:  1
     unique values:  20                       missing .:  0/680

              mean:   16.8647
         std. dev:    10.2225

       percentiles:        10%       25%       50%       75%       90%
                             7         7        13        30        32
```

5. List of cities and their observation year

Year	***City Code***	***City Name***
2003	NL512C1	Ede
2001	CY001C1	Lefkosia
2003	NL517C1	Hengelo
2011	PT017C1	Paredes
2003	NL515C1	Venlo
2003	NL519C1	Almelo
2003	NL516C1	Helmond
2011	IE005C1	Waterford
2005	SE005C1	Umeå
1997	FR202C1	Aix-en-Provence
2011	PT019C1	Póvoa de Varzim
2012	DE066C1	Kempten (Allgäu)
2003	NL513C1	Deventer
2007	FR027C1	Ajaccio
2007	FR093C2	Brive-la-Gaillarde
2011	UK038C1	Waveney
2004	IE004C1	Galway
2011	PT014C1	Viseu
2011	UK043C1	East Staffordshire
2001	DE520C1	Oldenburg (Oldenburg)
2011	PT016C1	Viana do Castelo
2011	ES059C1	Zamora
2011	ES046C1	Gandia
2006	DE544C1	Zwickau
2003	NL012C1	Breda
2007	FR073C2	Tarbes
2003	NL008C1	Enschede
2005	SE008C1	Örebro
2007	FR099C1	Fréjus
2003	NL520C1	Lelystad
2007	FR061C2	Niort
2007	FR096C2	Albi
2011	UK054C1	Cannock Chase
2001	DE517C1	Osnabrück
2008	ES020C1	Córdoba
2011	ES040C1	Talavera de la Reina
2011	UK015C1	Derry
2001	IT013C1	Cremona
2008	ES007C1	Murcia
2012	DE051C1	Villingen-Schwenningen
2011	UK542C1	Telford and Wrekin
2011	UK561C1	Torbay
2001	UK022C1	Wrexham
2011	UK565C1	Newcastle-under-Lyme
2001	IT026C1	Sassari
2011	ES062C1	Sanlúcar de Barrameda
2003	FR010C1	Montpellier
2011	UK568C2	Cheshire West and Chester
2003	NL014C1	Apeldoorn
2007	FR066C1	Saint-Brieuc
2007	FR063C2	Béziers
2007	FR090C2	Châteauroux
2007	FR059C2	Chalon-sur-Saône
2007	FR052C2	Saint-Nazaire
2011	UK035C1	Nuneaton and Bedworth
2007	FR046C2	Bayonne
2007	FR077C1	Roanne
2007	FR068C2	Vannes
2007	FR043C2	Perpignan
2011	BE010C1	Kortrijk
2011	UK060C1	Tamworth
2011	UK036C1	Fareham
2011	ES073C1	Elda
2012	DE078C1	Greifswald
2007	DE023C1	Moers
2012	DE055C1	Neumünster
2012	DE048C1	Wilhelmshaven
1998	FR009C1	Lille
2001	UK024C1	Worcester
2011	UK019C1	Lincoln
2011	PT008C1	Aveiro
2012	DE082C1	Dessau-Roßlau
2001	IT023C1	Potenza
2011	UK543C1	North East Lincolnshire
2012	DE060C1	Celle
2003	NL502C1	Zaanstad
2003	NL514C1	Alkmaar
2007	FR207C1	Lens - Liévin
2007	FR324C1	Martigues
2003	NL010C1	Heerlen
2007	FR067C2	Quimper
2011	UK517C1	Swansea
2011	UK051C1	Great Yarmouth
2003	NL013C1	Nijmegen
2007	FR057C2	Boulogne-sur-Mer
2003	NL006C1	Tilburg
2007	FR505C1	Charleville-Mézières
2006	DE514C1	Hamm
2001	IT016C1	Perugia
2011	UK046C1	Mansfield
2012	DE063C1	Plauen

1998	FR007C1	Bordeaux
2011	ES028C1	Reus
2001	IT019C1	Pescara
2011	ES508C1	Jerez de la Frontera
2011	UK555C1	Poole
2011	UK573C1	Bracknell Forest
2001	IT021C1	Caserta
2011	UK557C1	Blackburn with Darwen
2011	ES043C1	Ferrol
2011	UK536C1	Stockton-on-Tees
2011	UK057C1	Hyndburn
2011	UK531C1	Warrington
2011	ES060C1	Fuengirola
2011	ES533C1	Marbella
2011	ES029C1	Telde
2011	UK564C1	Warwick
2011	ES527C1	Jaén
2012	DE069C1	Rosenheim
2011	UK571C1	Cheltenham
2001	IT012C1	Verona
2012	DE080C1	Speyer
2011	ES031C1	Lugo
2012	DE059C1	Bayreuth
2003	NL511C1	Zwolle
2012	DE072C1	Friedrichshafen
2003	NL505C1	Maastricht
2007	FR214C1	Valence
2007	FR044C2	Nîmes
2007	FR104C2	Châlons-en-Champagne
2007	FR065C2	Bourges
2003	NL007C1	Groningen
2007	FR045C2	Pau
2003	NL506C1	Dordrecht
2007	FR062C1	Calais
2007	FR208C1	Hénin - Carvin
2007	FR049C2	Lorient
2012	DE536C1	Salzgitter
2011	FI007C1	Lahti / Lahtis
2003	NL005C1	Eindhoven
2007	FR039C2	Avignon
2007	FR053C1	La Rochelle
2011	UK575C1	Carlisle
2011	BE011C1	Oostende
2011	ES520C1	Castellón de la Plana/Castelló de la Plana
2011	ES074C1	Santa Lucía de Tirajana
2012	DE074C1	Görlitz
2001	IT020C1	Campobasso
2011	ES035C1	Torrevieja
2011	PT003C1	Braga
2001	ES017C1	Badajoz
2001	IT027C1	Cagliari
2011	UK505C1	Wigan
2011	ES506C1	Cartagena
2011	ES528C1	Lleida
2011	BE005C1	Liège
2011	ES034C1	Cáceres
2001	UK020C1	Gravesham
2011	UK574C1	Lisburn
2011	UK053C1	Hartlepool
2001	IT024C1	Catanzaro
2011	UK572C1	Gloucester
2011	ES037C1	Puerto de Santa María, El
2001	FR011C1	Saint-Etienne
2001	IT008C1	Bari
2011	ES044C1	Pontevedra
2011	ES054C1	Benidorm
2011	ES519C1	Albacete
2011	UK519C1	Barnsley
2011	UK062C1	Halton
2011	UK027C1	Stoke-on-trent
2012	DE070C1	Frankenthal (Pfalz)
2011	ES524C1	San Cristóbal de la Laguna
2011	ES532C1	Algeciras
2007	FR051C2	Troyes
2003	NL518C1	Schiedam
2007	FR024C2	Limoges
2007	FR082C2	Beauvais
2002	IE002C1	Cork
2012	DE079C1	Wetzlar
2001	UK021C1	Stevenage
2007	FR206C1	CA de Sophia-Antipolis
2007	FR056C1	Angoulême
2007	FR050C2	Montbéliard
2001	IT025C1	Reggio di Calabria
2001	IT010C1	Catania
2007	FR069C1	Cherbourg
2007	FR201C1	Aubagne
2011	UK528C1	Northampton
2004	IE003C1	Limerick
2011	UK044C1	Darlington
2001	DE504C1	Münster
2012	DE523C1	Paderborn
2011	ES041C1	Palencia
2011	ES514C1	Almería
2011	UK059C1	Redditch

2008	FI003C1	Turku / Åbo
2011	ES523C1	León
2001	IT005C1	Palermo
2011	ES505C1	Elche/Elx
2008	ES026C1	A Coruña
2011	UK050C1	Burnley
2011	ES068C1	Torremolinos
2011	ES050C1	Manresa
2008	BE004C1	Charleroi
2004	DE031C1	Schwerin
2012	DE071C1	Stralsund
2011	UK537C1	St. Helens
2011	UK549C1	Bedford
2011	ES057C1	Ponferrada
2011	ES072C1	Arrecife
2011	ES065C1	Línea de la Concepción, La
2011	ES053C1	Ciudad Real
2011	ES525C1	Tarragona
2011	UK566C1	Norwich
2001	UK017C1	Cambridge
2007	FR079C2	Saint-Quentin
2007	FR042C1	Dunkerque
2012	DE076C1	Neu-Ulm
2007	FR048C1	Annecy
2011	UK041C1	Ashford
2007	FR209C2	Douai
2011	UK047C1	Chesterfield
2007	FR064C2	Arras
2007	FR086C2	Evreux
2011	UK553C1	Blackpool
2007	FR506C1	Colmar
2011	UK503C1	Wakefield
2011	UK506C1	Doncaster
2011	ES529C1	Ourense
2011	UK045C1	Worthing
2011	UK548C1	Basingstoke and Deane
2011	UK533C1	York
2011	UK535C1	Swindon
2011	ES070C1	Irun
2011	ES011C1	Santiago de Compostela
2011	UK545C1	Peterborough
2011	UK540C1	Wycombe
2011	UK514C1	Rotherham
2011	UK558C1	Newport
2008	ES016C1	Toledo
2008	BE006C1	Brugge
2012	DE073C1	Offenburg
2011	UK518C1	Derby

2011	UK504C1	Dudley
2011	UK569C1	Ipswich
1997	FR203C1	Marseille
2011	UK559C1	Middlesbrough
2011	UK525C1	Milton Keynes
2001	DE528C1	Bottrop
2001	PT009C1	Faro
2011	ES032C1	San Fernando
2003	NL015C1	Leeuwarden
2012	DE064C1	Neubrandenburg
2011	UK031C1	Bath and North East Somerset
2007	FR032C2	Toulon
2003	NL011C1	Almere
2011	UK034C1	Thanet
2003	NL503C1	's-Hertogenbosch
2011	UK511C1	Bolton
2007	FR076C2	Belfort
2011	ES039C1	Avilés
2011	ES033C1	Girona
2001	UK023C1	Portsmouth
1991	FR016C1	Nancy
2012	DE065C1	Fulda
2011	UK539C1	Bournemouth
2011	UK554C1	Maidstone
2011	UK501C1	Kirklees
2011	ES071C1	Granollers
2011	BE009C1	Mons
2011	ES521C1	Huelva
2011	UK526C1	Rochdale
2011	PT015C1	Valongo
2011	ES516C1	Salamanca
2011	ES048C1	Guadalajara
2011	UK018C1	Exeter
2011	UK551C1	Falkirk
2000	FR030C1	Fort-de-France
2008	UK012C1	Belfast
2007	FR058C2	Chambéry
2003	NL501C1	Haarlem
2007	FR047C2	Annemasse
2007	FR036C2	Angers
2007	FR037C1	Brest
2003	NL504C1	Amersfoort
2007	FR034C2	Valenciennes
2008	ES012C1	Vitoria/Gasteiz
2007	DE537C1	Reutlingen
2011	UK516C1	Plymouth
2004	ES018C1	Logroño
2012	DE067C1	Landshut

2011	UK512C1	Walsall
2011	UK055C1	Eastbourne
2004	ES021C1	Alicante/Alacant
2011	ES045C1	Ceuta
2001	IT022C1	Taranto
2011	UK534C1	Bury
2011	ES015C1	Santander
2011	UK521C1	Oldham
2011	UK520C1	Southampton
2004	ES022C1	Vigo
2011	UK056C1	Hastings
2011	ES061C1	Cerdanyola del Vallès
2005	DE526C1	Wolfsburg
2011	ES055C1	Melilla
2012	DE045C1	Iserlohn
2007	FR012C1	Le Havre
2007	FR074C2	Compiègne
2007	FR060C2	Chartres
2011	UK061C1	Harlow
2007	FR021C2	Poitiers
2001	IT014C1	Trento
2011	ES515C1	Burgos
2011	ES530C1	Mataró
2006	DE547C1	Jena
2012	DE058C1	Lüneburg
2011	ES512C1	Terrassa
2001	ES006C1	Málaga
2011	UK562C1	Preston
2012	DE540C1	Siegen
2011	ES063C1	Vilanova i la Geltrú
2012	DE077C1	Schweinfurt
2011	UK556C1	Dacorum
2012	DE062C1	Bamberg
2008	SK007C1	Trnava
2009	DE021C1	Göttingen
2011	ES052C1	Rubí
2011	ES501C1	Granada
2008	DE508C1	Krefeld
2011	UK025C1	Coventry
2011	ES531C1	Dos Hermanas
2011	ES522C1	Cádiz
2012	DE061C1	Aschaffenburg
2012	DE534C1	Ingolstadt
2011	PT010C1	Seixal
2007	FR025C1	Besançon
2005	SE004C1	Jönköping
2007	FR035C2	Tours
2011	EE003C1	Narva
2011	UK026C1	Kingston-upon-Hull
2007	FR014C2	Amiens
2003	NL009C1	Arnhem
2005	SE007C1	Linköping
2007	FR040C2	Mulhouse
2011	UK016C1	Aberdeen
2011	ES075C1	Mollet del Vallès
2011	UK507C1	Stockport
2008	DE539C1	Cottbus
2008	ES023C1	Gijón
2008	ES013C1	Oviedo
2008	DE527C1	Bremerhaven
2011	UK532C1	Luton
2011	UK009C1	Cardiff
2011	UK524C1	Trafford
2011	ES507C1	Sabadell
2011	UK513C1	Medway
2001	DE039C1	Kiel
2003	DK003C1	Odense
2001	DE502C1	Mannheim
2004	DE035C1	Karlsruhe
2011	UK546C1	Colchester
2011	UK527C1	Solihull
2012	DE052C1	Flensburg
2001	IT017C1	Ancona
2012	DE542C1	Hildesheim
2011	PT504C1	Gondomar
2011	UK030C1	Wirral
2005	DE029C1	Frankfurt (Oder)
2012	DE056C1	Brandenburg an der Havel
2001	UK005C1	Bradford
2001	UK028C1	Wolverhampton
2011	ES056C1	Viladecans
2007	FR017C2	Metz
2009	DE543C1	Witten
2011	ES510C1	San Sebastián/Donostia
2004	ES004C1	Sevilla
2006	DE545C1	Erlangen
2012	DE525C1	Recklinghausen
2005	DE503C1	Gelsenkirchen
2011	UK523C1	Tameside
2009	DE505C1	Chemnitz
2001	UK011C1	Bristol
2011	UK014C1	Leicester
2011	UK508C1	Sefton
2006	DE042C1	Koblenz
2012	DE081C1	Passau
2011	ES049C1	Sant Cugat del Vallès

2011	UK502C1	North Lanarkshire	2004	DE022C1	Mülheim a.d.Ruhr
2011	UK522C1	Salford	2011	ES003C1	Valencia
2004	ES025C1	Santa Cruz de Tenerife	2012	DE511C1	Hagen
2005	DE530C1	Remscheid	2011	ES534C1	Torrejón de Ardoz
2011	BE007C1	Namur	2011	UK509C1	Sandwell
2011	PT508C1	Vila Franca de Xira	2011	UK040C1	Tunbridge Wells
2001	DE032C1	Erfurt	2003	DK002C1	Århus
2003	NL507C1	Leiden	2012	DE053C1	Marburg
2006	DE529C1	Heilbronn	2005	SE006C1	Uppsala
2007	FR018C1	Reims	2008	AT002C1	Graz
2007	FR019C1	Orléans	2011	FI002C1	Tampere / Tammerfors
2007	FR205C2	Nice	2011	BG011C1	Shumen
2007	FR022C2	Clermont-Ferrand	2001	PT505C1	Guimarães
2007	FR023C2	Caen	2001	IT007C1	Firenze
2011	ES058C1	San Sebastián de los Reyes	2004	ES014C1	Pamplona/Iruña
2011	UK510C1	Sunderland	2001	IT009C1	Bologna
2011	UK567C1	Slough	2012	DE054C1	Konstanz
2011	UK033C1	Guildford	2011	UK576C1	Crawley
2006	DE506C1	Braunschweig	2011	PT018C1	Barreiro
2011	ES036C1	Pozuelo de Alarcón	2001	DE020C1	Wiesbaden
2011	ES047C1	Rozas de Madrid, Las	2005	DE515C1	Herne
2011	ES064C1	Prat de Llobregat, El	2008	DE521C1	Neuss
2001	DE030C1	Weimar	2005	DE017C1	Bielefeld
2011	UK550C1	Dundee City	2011	UK052C1	Woking
2007	FR215C2	Rouen	2011	ES019C1	Bilbao
2008	BG007C1	Vidin	2007	FR004C2	Toulouse
2007	FR020C2	Dijon	2007	DE518C1	Ludwigshafen am Rhein
2007	FR038C2	Le Mans	2012	DE068C1	Sindelfingen
2005	DE510C1	Lübeck	2011	UK529C1	North Tyneside
2011	ES069C1	Castelldefels	2005	DE509C1	Oberhausen
2001	DE501C1	Duisburg	2001	PT501C1	Sintra
2011	ES042C1	Sant Boi de Llobregat	2011	UK560C1	Oxford
2009	DE533C1	Pforzheim	2011	ES030C1	Parla
2007	DE535C1	Gera	2008	BE002C1	Antwerpen
2011	ES511C1	Alcalá de Henares	2012	DE075C1	Sankt Augustin
2012	DE026C1	Trier	2001	UK003C1	Leeds
2001	DE538C1	Fürth	2011	UK547C1	South Tyneside
2007	DE541C1	Bergisch Gladbach	2012	DE044C1	Kaiserslautern
2011	ES067C1	Majadahonda	2001	ES009C1	Valladolid
2011	BE008C1	Leuven	2007	FR008C1	Nantes
2005	SE003C1	Malmö	2005	SE002C1	Göteborg
2007	FR213C1	Sénart en Essonne	2007	FR013C2	Rennes
2008	BE003C1	Gent	2011	BG006C1	Ruse
2001	PT007C1	Ponta Delgada	2008	DE010C1	Dortmund
2007	DE036C1	Mönchengladbach	2008	DE040C1	Saarbrücken
2012	DE057C1	Gießen	2011	UK538C1	Basildon
2011	UK544C1	Chelmsford	2012	DE519C1	Leverkusen
2006	DE516C1	Solingen	2006	DE524C1	Würzburg

2011	UK530C1	Gateshead
2001	IT015C1	Trieste
2012	DE046C1	Esslingen am Neckar
2011	UK032C1	Thurrock
2012	DE006C1	Essen
2012	DE047C1	Hanau
2011	ES010C1	Palma de Mallorca
2011	PT013C1	Odivelas
2011	BG016C1	Blagoevgrad
2007	FR006C2	Strasbourg
2011	UK552C1	Reading
2012	DE050C1	Tübingen
2011	ES066C1	Cornellà de Llobregat
2011	PT012C1	Almada
2001	PT503C1	Matosinhos
2011	UK541C1	Southend-on-Sea
2001	UK010C1	Sheffield
2001	PT006C1	Setúbal
2011	ES038C1	Coslada
2012	DE015C1	Bochum
2011	BG014C1	Haskovo
2007	FR026C2	Grenoble
2006	DE507C1	Aachen
2001	PT502C1	Vila Nova de Gaia
2001	IT001C1	Roma
2001	PT005C1	Coimbra
2012	DE546C1	Wuppertal
2008	BG008C1	Stara Zagora
2011	BG013C1	Yambol
2008	BG005C1	Pleven
2011	ES504C1	Móstoles
2011	UK029C1	Nottingham
2011	ES509C1	Fuenlabrada
2001	IT004C1	Torino
2011	UK563C1	St Albans
2012	DE049C1	Ludwigsburg
2004	IE001C1	Dublin
2011	PT011C1	Amadora
2008	DE532C1	Ulm
2011	BG009C1	Sliven
2001	UK002C1	Birmingham
2008	EE002C1	Tartu
2003	NL003C1	Rotterdam
2003	NL004C1	Utrecht
2009	DE027C1	Freiburg im Breisgau
2001	ES008C1	Las Palmas
2006	DE028C1	Regensburg
2011	UK006C1	Liverpool
2011	BG004C1	Burgas
2007	FR084C1	Creil
2011	ES518C1	Getafe
2005	DE018C1	Halle an der Saale
2001	IT003C1	Napoli
2011	ES535C1	Alcobendas
2011	UK515C1	Brighton and Hove
2007	DE034C1	Bonn
2005	DE008C1	Leipzig
2004	DE033C1	Augsburg
2004	DE009C1	Dresden
2001	UK008C1	Manchester
2007	DE025C1	Darmstadt
2007	FR003C2	Lyon
2011	BG015C1	Pazardzhik
2011	BG018C1	Vratsa
2011	ES503C1	Badalona
2008	DE037C1	Mainz
2008	BG003C1	Varna
2011	BG017C1	Veliko Tarnovo
2011	BG010C1	Dobrich
2007	FR310C1	CA de Seine Essonne
2011	BG002C1	Plovdiv
2001	DE019C1	Magdeburg
2006	DE014C1	Nürnberg
2008	DE012C1	Bremen
2011	ES513C1	Leganés
2008	DE043C1	Rostock
2011	BG012C1	Pernik
2007	DE041C1	Potsdam
2004	ES005C1	Zaragoza
2003	DK001C1	København
2005	DE522C1	Heidelberg
2007	DE004C1	Köln
2001	UK013C1	Newcastle upon Tyne
2003	NL001C1	's-Gravenhage
2007	FR309C1	CA du Plateau de Saclay
2007	FR305C1	Meaux
2003	NL002C1	Amsterdam
2009	DE531C1	Offenbach am Main
2001	IT006C1	Genova
2011	ES517C1	Alcorcón
2011	UK007C1	Edinburgh
2011	UK004C1	Glasgow
2011	UK117C1	Hillingdon
2007	FR304C1	Melun
2011	CZ018C2	Chomutov-Jirkov
2007	DE513C1	Kassel

2007	FR219C1	CA Europ' Essonne
2005	DE011C1	Düsseldorf
2007	FR311C1	CA du Val d'Orge
2011	BG001C1	Sofia
2008	DE013C1	Hannover
2007	FR306C1	Mantes en Yvelines
2007	FR518C1	Saint-Quentin en Yvelines
2004	LT001C1	Vilnius
2007	FR220C1	CA Brie Francilienne
2011	UK101C1	City of London
2011	UK129C1	Sutton
1990	CH010C1	Biel/Bienne
2007	FR308C1	Evry
2001	IT002C1	Milano
2001	PT002C1	Porto
2007	FR211C1	Versailles
2007	FR218C1	CC des Coteaux de la Seine
2001	DE005C1	Frankfurt am Main
2011	UK116C1	Havering
2008	DE007C1	Stuttgart
2001	IT011C1	Venezia
2007	FR223C1	CC de l'Ouest de la Plaine de France
2001	PT004C1	Funchal
2011	UK104C1	Bexley
2007	FR221C1	CA les Portes de l'Essonne
2004	ES024C1	L'Hospitalet de Llobregat
2011	CZ012C1	Kladno
2007	FR217C1	CA des deux Rives de la Seine
2007	FR504C1	Cergy-Pontoise
2007	FR224C1	CA le Parisis
2011	CZ014C1	Jihlava
2007	FR222C1	CA Val et Forêt
2011	UK121C1	Kingston upon Thames
2007	DE002C1	Hamburg
2007	FR323C1	CA de la Vallée de Montmorency
2004	FI001C2	Helsinki / Helsingfors
2007	FR216C1	CA Marne et Chantereine
2011	BE001C1	Bruxelles / Brussel
2004	SK004C1	Nitra
2007	FR313C1	CA Sénart - Val de Seine
2006	DE001C1	Berlin
2011	CZ017C1	Karviná
2011	UK118C1	Hounslow
2011	UK110C1	Enfield
2007	FR501C1	Argenteuil - Bezons
2007	FR312C1	CA du Val d'Yerres
2005	SE001C1	Stockholm

2007	FR512C1	CA des Lacs de l'Essonne
2008	ES002C1	Barcelona
2011	UK115C1	Harrow
2011	UK127C1	Richmond upon Thames
2011	UK106C1	Bromley
1990	CH008C1	Luzern
2005	DE003C1	München
2011	CZ013C1	Karlovy Vary
1990	CH005C1	Lausanne
2007	FR212C1	CC de la Boucle de la Seine
2001	PT001C1	Lisboa
1990	CH007C1	St. Gallen
2011	UK103C1	Barnet
2011	UK108C1	Croydon
2011	CZ008C1	?eské Bud?jovice
2001	EE001C1	Tallinn
2007	FR210C1	Marne la Vallée
2011	UK102C1	Barking and Dagenham
2012	CH006C1	Winterthur
2011	UK126C1	Redbridge
2004	SK003C1	Banská Bystrica
2011	CZ016C1	Most
2004	SK006C1	?ilina
2011	UK109C1	Ealing
2012	CH002C1	Genève
2011	CZ010C1	Pardubice
2011	CZ015C1	Haví?ov
2007	FR322C1	CA Val de France
2011	CZ009C1	Hradec Králové
2011	CZ007C1	Liberec
2001	ES001C1	Madrid
2011	UK124C1	Merton
2011	CZ011C1	Zlín
1990	CH003C1	Basel
2011	UK131C1	Waltham Forest
2011	UK105C1	Brent
2011	UK112C1	Hackney
1990	CH004C1	Bern
2001	SK005C1	Pre?ov
2011	UK111C1	Greenwich
2011	UK133C1	Westminster
2011	UK120C1	Kensington and Chelsea
2011	CZ004C1	Plze?
2011	UK130C1	Tower Hamlets
2011	UK119C1	Islington
2001	SK008C1	Tren?ín
2011	CZ003C1	Ostrava
2011	UK107C1	Camden

1990	CH001C1	Zürich
2011	UK113C1	Hammersmith and Fulham
2011	CZ005C1	Ústí nad Labem
2011	UK128C1	Southwark
2011	UK123C1	Lewisham
2011	UK132C1	Wandsworth
2011	UK114C1	Haringey
2004	SK002C1	Ko?ice
2011	CZ006C1	Olomouc
2011	UK125C1	Newham
2011	UK122C1	Lambeth
2007	FR001C1	Paris
2004	SK001C1	Bratislava
2011	CZ002C1	Brno
2011	CZ001C1	Praha