Factors Affecting Public Support of Transportation Policies: Using an International Survey and Hybrid Discrete Choice Modeling

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Abstract

What transportation policies do people support? What factors affect people's policy support? Detangling people's support of transportation policies is a way to understand public needs, to understand how the public evaluates and envisions the role of government in shaping the current as well as future urban transport system, and to anticipate difficulties of implementing certain types of policies due to public resistance. It is important to study policy support because 1) understanding public opinions can lend legitimacy and responsiveness to policy making processes and outcomes, and 2) characterizing people based on their support for different types of mobility policies may help customize policies for different groups so that the municipalities can enhance the effectiveness or equity of implementing certain types of policies.

This thesis models the factors that contribute to stated support of 11 different transportation policies in an international sample of 41,932 individuals in 51 countries/regions using the utility-maximizing approach of hybrid discrete choice. It analyzes transportation policy support expressed by individuals in the survey, with respect to their socio-demographic characteristics, travel modes, and attitudes. We find that across the globe, different age, gender and income groups prioritize policies differently and that generally individuals support policies that benefit their most typical transport mode positively. Moreover, by controlling for individual characteristics, a country-level analysis attempts to capture differences of policy support resulting from being of different nationalities. The results suggest that many countries share similarity in their policy support with other countries that are geographically adjacent, but there are also unexpected country peers that are far removed geographically, but have similar policy support. Overall, the methods and findings of this thesis may be useful for policymakers working on evaluating policy effectiveness for certain social groups and for researchers looking at what policy paths towards sustainable transportation that different countries might take.

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Content

List of Tables

List of Figures

1 Introduction

1.1 Background

1.1.1 Intriguing Problem

Transport sector's carbon dioxide (CO_2) direct emissions increased 29% globally from 5.8 to 7.5 gigatons between 2000 and 2016. In 2016, transport produced about 23% of global energy-related CO_2 emissions. As of 2014, 14% of global greenhouse gas (GHG) emissions result from transport (SLoCaT, 2018). Transportation is now the third largest source of global greenhouse gas (GHG) emissions, following the power sector and other industrial combustion (SLoCaT, 2018).

In 2016, the United Nations (UN) announced that 17 Sustainable Development Goals (SDGs) in Figure 1.1 of the 2030 Agenda for Sustainable Development, adopted by countries in 2015, officially entered into force. With these new Goals that universally apply to all, countries will mobilize efforts to end poverty, fight inequalities and tackle climate change (*The Charter for Compassion and the Sustainable Development Goals*). Accomplishing the SDGs has to rely on advances in mobility (the World Bank, 2017). For example, SDG 13 reducing GHG emissions, SDG 11 sustainable cities, SDG 15 biodiversity, SDG 3 good health and wellbeing cannot be achieved without sustainable transportation (the World Bank, 2017).

Figure 1.1 17 SDGs by the United Nations (source: *the Charter for Compassion and the Sustainable Development Goals)*

SDG target 11.2 is directly transport-related: by 2030, providing access to safe, affordable, accessible and sustainable transportation systems for all, improving road safety, notably by expanding public transportation, with special attention to the needs of those in vulnerable situations, women, children, disabled and older persons. (the World Bank, 2017)

Sustainable transportation has to be put on the agenda to meet the SDG goals. Many countries and cities have adopted various policies to achieve the goals—for example—car restriction, public transit expansion and active transportation. There are in fact many policy alternatives to address sustainable transportation.

This thesis focuses on public support and acceptance of transportation policies, as a way to promote sustainable transportation policies. The reason is that gaining public acceptance remains a major barrier to policy implementation (Rentziou et al., 2011). The promotion of sustainable transportation challenges the established dominance of motor vehicles and therefore faces obstacles such as the predominance of car-oriented transportation infrastructure, political systems and institutional structures that prioritize road-building. To address one of these barriers—public resistance—researchers, policy makers and advocates need to have a better understanding of sustainable transportation policy interventions that have substantial public acceptance and support.

1.1.2 Overall Trend – Sustainable Transport Alternatives

The approaches to deal with transportation problems like congestion, air pollution, long commuting time, etc. could be either coercive or noncoercive. Garling and Schuitema (2007) evaluate coercive and noncoercive approaches toward the reduction of car use in metropolitan areas and found that necessary but unpopular coercive measures may become more acceptable when they are combined with noncoercive measures such as providing attractive travel alternatives and public communication programs.

Among the many policy options, restricting car use may be the most direct (but often coercive) measure to cut down demand. These restrictions can be imposed through financial disincentives or regulatory mandates. London is well known for its congestion charge that restricts vehicle use in the city center: a fee of £11.50 is imposed for driving a vehicle within the charging zone each weekday between 07:00 and 18:00 (*Transport for London, 2019*). Beijing has restricted cars on roads according to the last digit of the plate number since 2008 for the Olympics and the once ad-hoc policy has been readopted nine times in the recent ten years (*Xinhua 2018*). Many other Chinese cities have imposed a range of car usage restrictions, from the strict license plate restrictions to less stringent restrictions by type of vehicle, time of day, or for special occasions.

When demand on mobility still increases, it has to be met by other means, such as alternative transportation modes. Micro-mobility services, such as shared bikes and e-scooters, emerged in recent years and had accelerated growth in 2017 (SLoCaT, 2018). The infrastructure determined by new policies thus responded to those emerging needs. For example, the statistics from Boston Department of Transportation show that its bike network in Boston was 55 miles in 2008 and 120 miles in 2013; it plans to reach 195 miles in 2018 and 356 miles in 2043 (*Boston Bike Network Plan Fall* 2013).

New technologies make the motorized travel less environmentally harmful and many countries are subsidizing clean energy vehicles to reduce the negative impact of fuel-based vehicles. Electric vehicles (EV, referring to electric battery passenger cars), have grown from one million in 2015, to two million vehicles a year later in 2016, and three million by 2017 (SLoCaT, 2018). Within the market, Asian, Europe and North America are the largest three players of global EV fleet and the three take market shares 47%, 27% and 26%, respectively in 2017 (SLoCaT, 2018). Within Europe, the Nordic region – Denmark, Finland, Iceland, Norway and Sweden – the stock of EV accounted for roughly 8% of the global EV fleet in 2016 and measures such as subsidizing EVs that reduces the purchase price were the main driver (*Nordic EV Outlook* 2018).

Subsidies towards clean-energy vehicles or the provision of more sustainable alternative transportation options, such as public transit and bike lanes, are examples of noncoercive policies that represent a different approach for policy makers to improve the current transportation condition. Because they aim to expand rather than constrict individual choice, they may be more easily accepted and supported by the public. The next question would be how policy makers choose from the choice set of policy alternatives to make policy introduction effective and acceptable.

1.1.3 Public Policy Making

When talking about diverse policies that approach problems with different intervention strategies, it is useful to have a common framework of policy study. The study of policy making is the study of behavior and its consequences: the behavior of individuals, groups, and organizations that produce or mediate the social conditions to which policy makers react (Lynn 1986).

Policies need to address the common dilemma that numerous individually optimal decisions may combine into a collectively suboptimal situation, like exploitation of resources, etc. (Vlek and Steg, 2007). It is therefore useful to tackle the individual behavior and therefore aggregated behaviors to inform policy analysts about the incentives of actors' action. Changes in human behaviors may be encouraged by addressing the knowledge, beliefs, and preferences of individuals and groups (Vlek and Steg, 2007). More thorough literature review will be provided in Chapter 2, where I delineate the definition of public opinions, the importance of studying public opinions in decision making and specific factors that affect acceptance in transportation policies. Here, my study on policy support for transportation is a small piece of the overall public policy study, but transportation is an evolving and practical field with numerous societal challenges. This thesis in particular aims at public support of transportation alternatives using data from an international mobility survey.

1.2 Motivation

For decades, governments have talked about sustainable transportation; we also witness some emerging new forms of transport like Transportation Network Companies (TNCs) from the private sector. However, though sustainable transportation policies are often crafted for the benefit of society, it is often difficult for people to accept the implementation. For example, the debate about congestion charging occurred around 1990 in the U.S. but still the idea was being against largely by the public. Planners and government officials need to have people buy into their policies. Otherwise, enforcements are costly and leaders will encounter political pressure from their constituents.

Implementing policies is a tortuous process. Obtaining the knowledge about what type of policies that individuals and groups support could help policy makers propose policies that accurately target specific population or that have a realistic expectation of implementation due to public support.

1.3 Research Objectives

What transportation policies do people support? What factors affect people's policy support? Detangling people's support of transportation policies is a way to understand public needs, to understand how the public evaluates and envisions the role of government in shaping the current as well as future urban transport system, and to anticipate difficulties of implementing certain types of policies due to public resistance. It is important to study policy support because 1) understanding public opinions can lend legitimacy and responsiveness to policy making processes and outcomes, and 2) characterizing people based on their support for different types of mobility policies may help customize policies for different groups so that the municipalities can enhance the effectiveness or equity of implementing certain types of policies.

This thesis models the factors that contribute to stated support of 11 different transportation policies in an international sample of 41,932 individuals in 51 countries using the utility-maximizing approach of hybrid discrete choice. It analyzes transportation policy support expressed by individuals in the survey, with respect to their socio-demographic characteristics, travel modes, and attitudes. Moreover, by controlling for individual characteristics, a country-level analysis attempts to capture differences of policy support resulting from being of different nationalities. Overall, the methods and findings of this thesis may be useful for policy makers working on evaluating policy effectiveness for certain social groups and for researchers looking at what policy paths towards sustainable transportation that different countries might take.

The purpose of this research is thus to understand pubic opinions about mobility-related policies. We detangle what characteristics of people relate to what types of policy support. This knowledge can help enrich the study of transportation policy. It could also help transportation engineers, planners and policy makers use the findings to design policy schemes that are suitable and would be accepted by the public.

1.4 Research Questions

Specifically, this thesis seeks to answer two related research questions regarding support of transportation policies. The first research question is interested in variation in policy support across individuals, while the second research question looks at variation in policy support across countries.

Question 1: What individual characteristics affect policy support?

Some of my hypotheses include: people with higher education tend to support more sustainable policy options; people are self-interests driven and tend to support policies that improve the services of the mode they currently use; people with high car pride would not support policies that improve alternative modes. I will test and comment out those hypotheses in Chapter 4 individual-level analyses.

Question 2: Do people of different countries support different policies? What characteristics of countries affect country-level policy support?

Different countries may present different patterns on transportation service provision. For example, it is well-known that Nordic countries have been investing much in green transport like biking and walking. Residing in one country can affect a person's mobility policy support to certain degree, due to the national culture, ideology and many other social, economic and environmental conditions that individuals are exposed to.

1.5 Research Approach

To answer the research questions above, we adopt a hybrid discrete choice modeling approach with latent variables using data from an international survey. There are 11 policy items where respondents can choose up to three to support. The core question used in the survey is the one asking people to choose up to three mobility policy items to support, out of 11 options in total. The exact wording of the question is "If the government decides to improve overall transportation conditions in your location, which of the following policies would you support? Please select up to three." The 11 policy items are, "Build additional roads", "Discourage the use of private automobiles in the city center", "Expand bike lanes", "Expand public transportation services (bus/train)", "Improve pedestrian facilities (sidewalks, street crossings etc.)", "Introduce car-free pedestrian zones in the city center", "Lower public transportation fares", "Prioritize public bus lanes and/or bus rapid transit", "Provide clean energy-based public transportation options", "Provide more parking spaces", and "Subsidize clean energy vehicles".

Therefore, 11 independent models were built to reflect the binary choice (1: choosing the policy item as one of the polices to support and 0: not choosing), with respect to a series of explanatory variables including socio-demographics, travel mode, etc. that were either surveyed by the questionnaire or supplemented by other datasets drawn from outside sources. Chapter 3 describes the survey data and modeling approaches in detail.

1.6 Research Structure by Chapters

The rest of the thesis is structured as follows. Chapter 2 reviews relevant literature on the definition of public opinion, importance of recognizing public opinion, and specific findings of variables that affect public acceptance regarding transportation-related and non-transportation related policies. Chapter 3 includes a detailed description of the dataset and methodology. The modeling results for each of the two levels of analysis—individual and country—are divided into two separate chapters. Chapter 4 includes individual level model results and interpretations with respect to policy implications. Chapter 5 includes country level model results and interpretations. Chapter 6 describes an alternative modeling approach that deals with the "up-to-three" survey choice limitation. Lastly, Chapter 7 summarizes the major findings of the thesis and discusses limitations of this thesis work and directions for future research.

2 Literature Review

In this chapter, I define public opinion, discuss why we care about public opinion, and explore how public opinion is studied in regards to transportation and non-transportation policy acceptance.

2.1 Public Opinion and Politics

2.1.1 Definitions of and Distinctions among Attitudes, Beliefs, Opinions

It is useful to first define and distinguish a few terminologies before we use the phrase "public opinion" in this study. In this thesis, I define individual policy support as opinion or beliefs, and those beliefs or opinions by groups as public opinion. This choice results from a review of basic definitions of the words *attitude*, *belief*, and *opinion* (Oskamp & Schulzt, 2005), as detailed below.

The first basic term to define is *attitude*. Attitude is commonly known as the posture of the mind (Oskamp & Schulzt, 2005). Or it can be defined as any mental position with regard to a fact or a state (Merriam-Webster). Also, attitude is the fundamental motivation of the behavior and indicates a person's readiness to respond (Allport, 1935). "An attitude is a predisposition to respond in a favorable or unfavorable manner with respect to a given attitude object" (Oskamp & Schulzt, 2005). In this study, we can reasonably paraphrase the survey question as people hold supportive attitudes toward certain policies. Thus, a person may respond to the policy in a favorable manner if he/she holds positive attitudes with respect to that policy.

Other very similar terms are *belief* the o*pinion*, which are value judgments of an object. Beliefs are more cognitive, like thoughts and ideas; whereas attitudes describe feelings and emotions (Oskamp & Schulzt, 2005). In many circumstances, the two words, beliefs and attitudes, are interchangeable, especially if the beliefs are evaluative beliefs. One example is that an evaluative belief "my boss is a nice guy" and an attitude "I like my boss" eventually convey the similar idea. A person's attitude toward an object summarizes his or her evaluative beliefs about the object (Oskamp & Schulzt, 2005). In most cases, opinions are equivalent to (evaluative) beliefs (Oskamp & Schulzt, 2005), so I do not plan to distinguish the two terms further here. In terms of the policy items in this thesis, individuals' policy support like "I support expanding bike lanes" or "I support building additional roads" can be regarded as indicative of attitude, belief, or opinion.

Next, there comes the necessity to define the term *public opinion*, as we are interested in shared opinions of groups of people with respect to their characteristics. The phrase public opinion is widely used to describe the shared attitudes and beliefs of large segments of a society (Oskamp

& Schulzt, 2005). But there has been debate over the proper and complete definition for more than 200 years. In general, the large segment of people (also called the public) has to have some defining characteristics in common—for example, all registered voters in Massachusetts or the same racial group in a county. However, others have argued that it is unnecessary to impose many specifications in defining public opinion, such as the particular public/groups of population involved, the extent of consensus, etc. (Childs, 1965). In other words, the restriction and specification on the "large segments of the society" can be relaxed and "the study of public opinion is, therefore, the study of collections of individual opinions wherever they may be found" (Childs, 1965). For this research, we adopt Childs's definition of public opinion because of its breath and lack of restrictions.

Therefore, to make the analysis consistent, I will argue that commonly used term like attitudes, beliefs or opinion are all possible words to characterize policy support of a single person. Findings of policy support will fit into the framework of attitudes, beliefs and opinions. The term *public opinion* is reserved to describe the belief or opinions of a group of people, no matter whether the group is composed of citizens of a particular country, or of females across countries. By Childs's definition, all those groups' opinions can be characterized as public opinion.

2.1.2 Why We Study Public Opinion

The next essential question is why we care about public opinion in the domain of public policy. There are three perspectives about why and how public opinion affects public policy.

Oskamp and Schulzt (2005) discuss how public opinion affects public policy in the context of democratic governments, particularly the United States. First, the "will of the people" dictates that political administrators, the civil servants, should make their decisions in accordance with the opinion of the public, or their constituents to be specific. This idea originated from Jean-Jacques Rousseau's *The Social Contract*, and was strongly supported by Thomas Jefferson. The second point derives from the first one, but instead requiring that the representative's vote should be based on their judgment, rather than the popular clamor. This position was prominently espoused by the British parliamentarian Edmund Burke and by Alexander Hamilton in *The Federalist Papers*. The third viewpoint is the "party responsibility" approach, which suggest that representatives are responsible, not to his or her own local constituents, but to the program developed by his or her party, designed to satisfy the needs of the whole nation. All the three points indicate how policymakers can respond to public opinion, either directly (in terms of responding to constituents) or indirectly (in terms of responding to one's own judgment or party views). The degree of policy response to the public views vary under different political framework and political structures, but public opinions can, theoretically, inform the directions of party and national programs.

As for the effects of public opinion on policy making, scholar have observed that legislators vote more closely to the public opinion in the year before their next election than at other times in the electoral cycle (Kuklinski, 1978; Thomas, 1985). When it comes to transportation policy making, there are many examples of changes to toll roads during the election year that were made to gain voters' support. One such example was I-405 in Washington State, USA; before the election in 2016, Republican representative in the state legislature Harmsworth attempted to revert one toll lane in each direction to a general-purpose lane and also abolish tolling completely (*I-405 Tolls Poised to Become Election Year Issue*, 2016). At the meantime, Democrats focused on benefits to transit riders and Republicans were emphasizing the cost to drivers. Those approaches largely correspond to their voters' opinions, which are amplified and influential at certain moments.

However, not every country in the globe operates within a democratic framework. Even if very different governmental frameworks, interest in public opinion exists. For example, public opinion polling has spread to Russian and the formerly communist countries of Eastern Europe, despite common misconceptions that citizens' personal viewpoints are absent in the government's decision making (McIntosh & Hinckley, 1992; Crespi, 1997). China, another communist nation and always critiqued as ignoring public voices, is expanding the role of public participation and public opinion in the policymaking process. Li and de Jong (2017) suggests that the public participation is not well institutionalized in the strategy development due to the distinctive top-down mode of decision making in China. However, Chinese municipalities now reveal plans regarding new designs, construction or other civil/social issues and weigh public opinions before the government makes the final decisions. Therefore, public participation and public opinion gathering occurred more in the implementation phase of government policies, plans, or projects (Li, Ng, and Skidmore, 2012). Chun et al (2018) conducted interviews in Beijing and Shanghai regarding government officials' policy making contributor, obstacles and process and found that public opinion can provide impetus for policy formation, but that public complaints can be an obstacle in policy decision making.

No matter the political structure, with more access to the information and channels to make voices heard, nowadays, the public can participate in the public policy discussion more and the administrators should take the public viewpoint and make policies that help achieve the goals set by the people and party programs; or on the other hand, make the implementation process easy. Therefore, public opinions have the value influencing public policy making.

2.2 Socio-demographic Predictors of Policy Support

Next, we consider studies of public opinion towards different policies to obtain a sense of how the public views public policies and what characteristics of individuals are likely to significantly affect their policy preferences. The literature review will go over studies of both transportation and non-transportation policies with respect to individual socio-economic-demographic characteristics, travel modes, etc.

2.2.1 Non-transportation Policies

One example about trade policy is worth examining because the standard model of trade policy making always takes individual preferences as an important element (Scheve, et al. 2000). Trade policy preferences depend on how trade policy affects income and production, and income is a proxy for individual economic welfare. Scheve, et al. (2000) first found that lower skill, measured by education or average occupation earnings, is strongly correlated with support for new trade barriers; while employment in industries more exposed to trade, measured by tariff rates or net exports, is not. The contribution of this empirical study is that it includes other asset variables since income can be saved and invested as ownership of assets. Thus, the article provides new evidence on the determinants of individual trade-policy preference and concludes that home ownership also matters for individuals' trade-policy preferences.

Another study on labor market competition and individual preferences over immigration policy suggests that low-skilled labors prefer limiting immigrant inflows to the U.S., but the relationship between skills and immigration options is not stronger in high-immigration communities (Scheve and Slaughter, 2001). Like the first study on trade policies, skills are highly correlated with income and thus economic wellbeing, and the study of individual policy preferences provides lens to analyze individual wellbeing under the proposed scenarios. Non-economically, the policy preferences also reflect the public's ideology and value. From the two perspectives, obtaining understandings of public opinions on policy preference helps policy makers assess how new policies potentially affect the public's wellbeing status, lifestyle, value, etc.

2.2.2 Transportation Policies

There is a considerate amount of literature on pricing schemes of policies as well as how people's characteristics affect their perception, attitudes and therefore acceptance of congestion charging and other transportation policies. On early study looked at transportation attitudes, behaviors, and transportation policy preferences in Orange county, California from 1980-1989, a suburban region during an era of rapid growth and industrialization (Baldassare, 1991). Despite the fact that forty percent of residents selected transportation and traffic as the most serious problem in the county—a percentage way higher than other issues like crime, housing, schools, etc. —residents exhibited little change in travel behavior (e.g. commuting modes) and considerable opposition to new transport policies aiming at congestion relief (Baldassare, 1991). Furthermore, the study looked at whether political factors (being a republican or not), demographic factors (age, gender, income, etc.) or commuting behaviors correlated with support for a gasoline tax increase and three additional policy scenarios intended to reduce automobile uses and improve air quality: introducing parking fees for single drive to encourage carpool, promoting job-housing balance, and having larger employers' incentives for ride-sharing/mass transit use. In many cases, notably support of an increased gas tax, political factors, demographic factors, and commuting behaviors were not significant predictors of policy support. The only evidence that transportation behavior is related to policy preferences is the distance of driving alone to work leading to opposition to carpooling. This makes sense as long-distance commuters are less likely to find carpool partners or less willing to share the long ride with strangers. The demographic variables suggested that high household income is significant in predicting opposition to parking fees to encourage carpooling. Opposition to the job-housing balance proposal was found to increase with age and income; while opposition to the proposal of ridesharing incentives by larger employers increased with age, full-time work status, and Republican affiliation.

Those findings on travel behaviors and policy preferences revealed unique mobility patterns and perceptions in Orange County, California, back in 1980-1990 period. One overall thought is that affluent suburbanites resist policies that require financial or lifestyle sacrifice. Given both of the commuting mode variables and social-demographic variables are to some degree similar and available in our international sample, Baldassare's work set the foundation of modeling the relationship among such variables.

Additionally, Rentziou et al. (2011) researched public perception and acceptance of road pricing, using an empirical study in Athens, Greece. They found that trip characteristics, sociodemographic characteristics, perceived consequences of traffic congestion, and allocation of congestion pricing revenues influence public acceptance of congestion pricing. Findings include that respondents who traveled to the pricing area by taxi and respondents with higher educational levels were more likely to accept congestion pricing; while respondents younger than 44 years old and those who traveled by car or by motorcycle were less likely to accept congestion pricing. Therefore, this study found clear connections between current travel behavior and socio-demographics on individual's policy support.

While many policy preference studies in the transportation domain (such as those summarized above) consider a specific geographical region, some studies do expand the research question to compare across contexts. Kim, et al. (2013) investigated attitudes toward road pricing and environmental taxation among US and UK students. The comparison arrives at conclusions that U.K. car owners assess road pricing as less fair and report less trust in the London government. Considering sociodemographic variables, gender has a negative effect on issues of trust in government in the U.K. and perceived effectiveness in the U.S., meaning that it is more difficult to gain acceptability for road pricing from women compared to men in both countries.

2.3 My Contributions

Again, it is important to note the difference in scale and in scope of the previous mobility policy studies and this thesis. The surveys focusing on specific areas approximate reality and can validate the policy framework with targeted ground truth data. Also, emphasizing on pricing enables transportation engineers and policy makers to use the estimation findings to design a pricing scheme that is suitable for the study area and would be accepted by the public (Rentziou et al. 2011). My works intends to extend the knowledge of policy support both to a greater area and to larger number of policy items. In fact, none of the policy support items are about congestion charging or road pricing. My thesis will go beyond the setting of mobility culture in American suburbia in 1990 and though less concrete in terms of the financial capabilities embedded in the policy items, the 11 policies in the survey proffer a larger choice set of policy preferences that contribute to the knowledge of mobility policy support study in general. Some of the findings from the previous literature would be local phenomenon, like elder people tend to oppose ridesharing in the Orange County; but maybe it is not. The mobility study with the use of Dalia survey will contribute to the mapping of the global opinions and the cross-country differences. The new dataset offers new opportunities to measure public opinions cross many population groups and expands breadth to the policy implications.

3 Dataset Description and Model Specification

3.1 Dataset Description

An international survey was distributed in 52 countries/regions during December, 2016 to February, 2017. The dataset was collected by Dalia Research (https://daliaresearch.com/) under the collaboration with MIT Energy Initiative Mobility of the Future research consortium. The survey was mobile phone based and respondents were recruited through a variety of ad-exchanges, apps, and websites. When browsing related content on their mobile devices, individuals were prompted to take the survey and were offered rewards in the form of virtual currencies, for example, game money, prepaid credits and others. So, the respondents volunteered and were compensated.

Dalia Research performed quota sampling to ensure sample representativeness by age and gender for each of the 52 countries/regions. The quotas were calculated based on the U.S. Census Bureau's International Data Base, adjusted to match the internet-connected population. There are 42,972 individuals in the survey (with a sample size ranging from 200 to 1000 per country): the sample size is around 1000 for some large countries and 500 for smaller ones, while Hong Kong, with 208 responses, has the smallest sample size. Note that Taiwan does not have national statistics published on the World Bank dataset; for the consideration of legitimacy of the data comprehension on country level (which I will cover in the later sections), I did not include Taiwan in the final dataset. Therefore, I dropped 1,040 individuals from Taiwan and the final data size is 41,932.

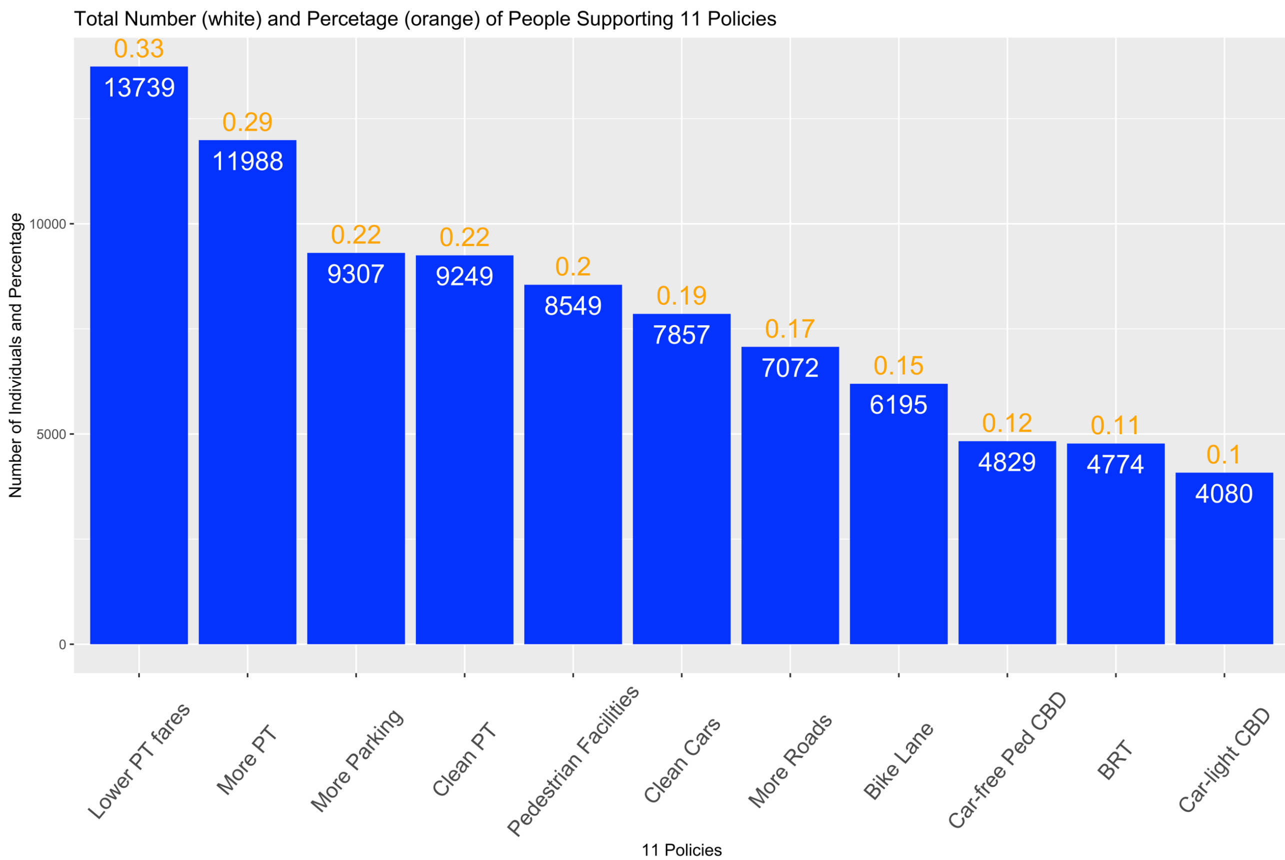
The survey asked people's socio-demographic characteristics as well as mobility behaviors, attitudes, and perceptions regarding a variety of mobility-related options. The specific information obtainable from the survey includes individuals' location, the size of the residing township, age, gender, education, monthly household income, car ownership, commuting modes, commuting time, attitudes towards owning and using a car, etc. The core question used in the survey is the one asking people to choose up to three mobility policy items to support, out of 11 options in total. The exact wording of the question is "If the government decides to improve overall transportation conditions in your location, which of the following policies would you support? Please select up to three." The 11 policy items are, "Build additional roads", "Discourage the use of private automobiles in the city center", "Expand bike lanes", "Expand public transportation services (bus/train)", "Improve pedestrian facilities (sidewalks, street crossings etc.)", "Introduce car-free pedestrian zones in the city center", "Lower public transportation fares", "Prioritize public bus lanes and/or bus rapid transit", "Provide clean energy-based public transportation options", "Provide more parking spaces", and "Subsidize clean energy vehicles".

Therefore, it is a stated preference survey study, but a single person can have zero, one, two, or three choices. To help read, I include the 11 policies with abbreviations in Table 3.1. A helpful statistic of the number of individuals "voted" on each policy support item and the percentage are given in Figure 3.1.

Table 3.1 11 Policies where respondents can choose up to three to support.

Index	**Policy Labels**	**Actual Policy Items**
A	More roads	Build additional roads
B	Car-light CBD	Discourage the use of private automobiles in the city center
C	Bike lanes	Expand bike lanes
D	More PT	Expand public transportation services (bus/train)
E	Pedestrian facilities	Improve pedestrian facilities (sidewalks, street crossings etc.)
F	Car-free ped CBD	Introduce car-free pedestrian zones in the city center
G	Lower PT fares	Lower public transportation fares
H	BRT	Prioritize public bus lanes and/or bus rapid transit
I	Clean PT	Provide clean energy-based public transportation options
J	More parking	Provide more parking spaces
K	Clean cars	Subsidize clean energy vehicles

Figure 3.1 Number and percentage of each policy being chosen in the entire international sample.



The percentage here can be interpreted as the percentage of people who choose to support a certain policy as one of their top 3 policy priorities. Since people can choose more than one policy to support, the percentages do not add up to one. The support of "Lower public transportation fares" has the highest popularity, as 33% of respondents choose it as one of the top 3 policies they support. The second most popular policy is "Expand public transportation services (bus/train)" with 29% of individuals in the survey prioritizing the policy in their top three choices. This is followed by "Provide more parking spaces" chosen by 22% of individuals. A reminder that not choosing a policy, X, does not mean people would not support X, but simply that X is not within people's priority list. This means that a NO-answer could indicate a lower level of support, but not necessarily an opposition.

3.2 Global Mapping and IPF Technique

A global map is helpful for readers to get an intuitive picture of the dataset coverage and response pattern. The figures below show aggregated weighted sample percentage of supporting different policies. To make the results relatively representative of the countries' true condition, we adopted iterative proportional fitting (IPF) technique to adjust the data table cells such that they add up to selected totals for all dimensions of the table (Hunsinger, 2008). In our case, the dimensions are age, gender and city size. We had a series of weights assigned to each individual based on the person's gender, age and city size, to fit to the national distribution: percentage of female and male, percentage of age 15-24, 25-34, 35-49 and 50+ and percentage of people living in cities having more than 1 million population. We admit that it would be ideal to have fit individuals' household income to national-level income distribution, as income is supposed to be a strong indicator to attitudes and behaviors, but such national income distribution information is unavailable from our search. We therefore used the percentage of people living in a large city as a proxy to income effect and assume rich people can afford to live in mega-cities in many cases. All the nation-level statistics were obtained from the World Bank Data website.

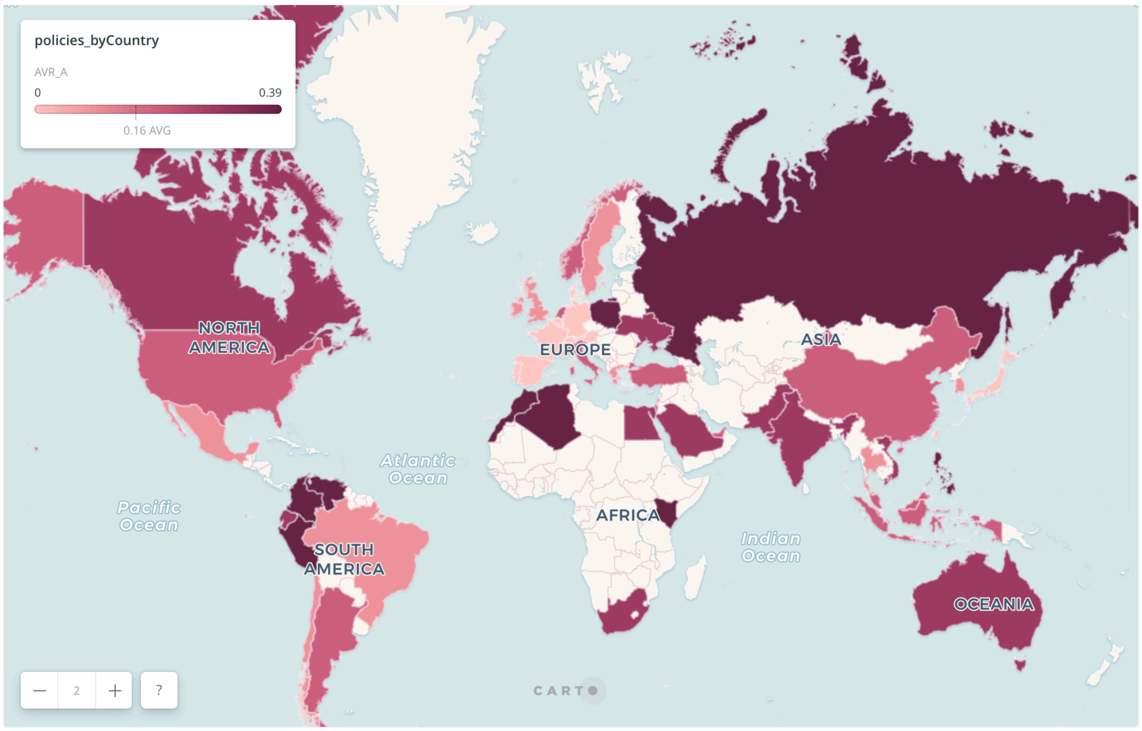
Therefore, we have weights assigned according to individuals' gender, age and city size by those variables' distribution in his/her own country. However, note that Hong Kong and Singapore are city-states and therefore all responses in the two places should report that their city has more than 1 million population. On the contrary, Bahrain and Norway do not have cities larger than 1 million people. We want to select those countries that we know the urbanization rate and only calculate weights based on gender and age dimensions.

Therefore, if we multiply weights obtained by IPF and the policy support (1/0), we can get weighted support. If the individual in the survey is over-representing population group of young males in large cities, for example, his weight will be lower than one and thus his support would be less dominant in representing national pattern. If an individual is of, for instance, older female population that is under-surveyed, she will be assigned a large weight (>1) so that her opinion will be more pronounced to represent the country's public view.

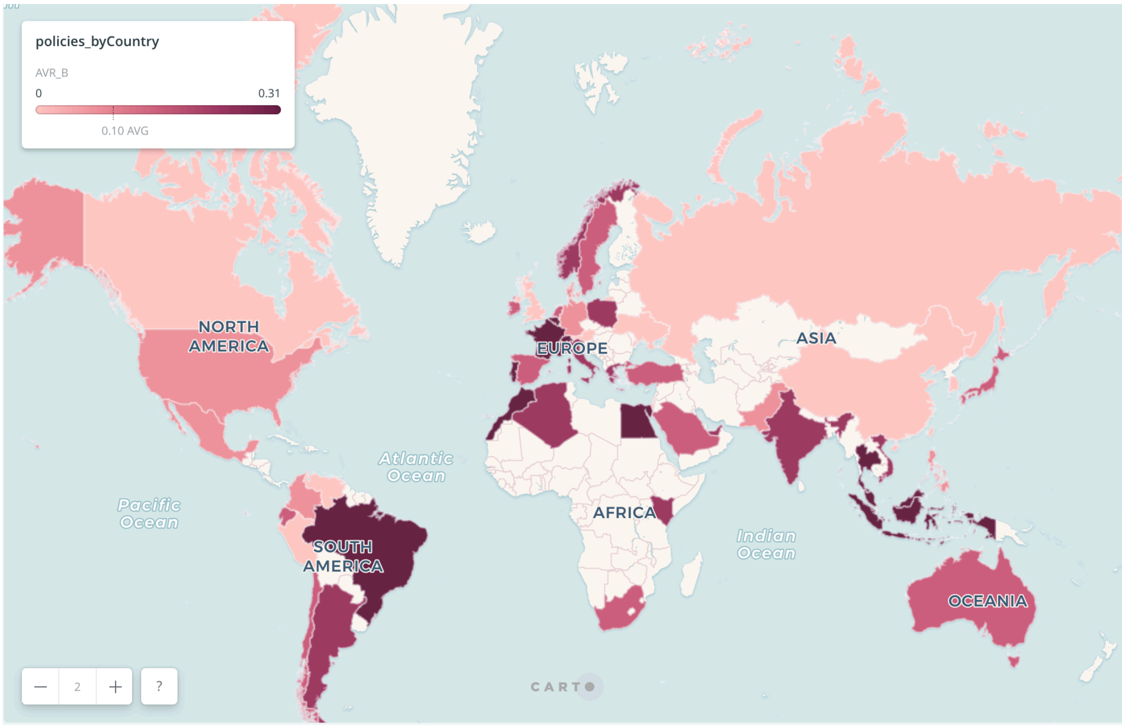
Then we could aggregate the support within countries, for example, taking an average, to thus approximate a national support level of policies. This is what the global mapping below shows. In Figure 3.2, for example, the percentage of supporting (a) building more roads within people's top 3 choices is higher in countries like Russia, Algeria, Colombia, etc. But the percentage of suporting (d) expanding transit services as one of the 3 top choices is higher in Australia, Denmark, Oreland, etc. The glimpse of the globe map shows that the two policies exhibit different pattern. In another word, people in different countries view policies differently for their top three choices. Similarly for other policy items, countries do exhibit different patterns (variances) as well. Note that in the maps, the scales across the 11 policies are not the same. The quantile binning strategy of percentage of support by countries on each policy highlights the contrast among countries. Using a uniform range for coloring will lose nuances in contrasts.

Figure 3.2 11 Policies shown by percentage of support across countries—aggregated weighted sample percentage of support of the policy as one of the top 3 policy items that people would support.

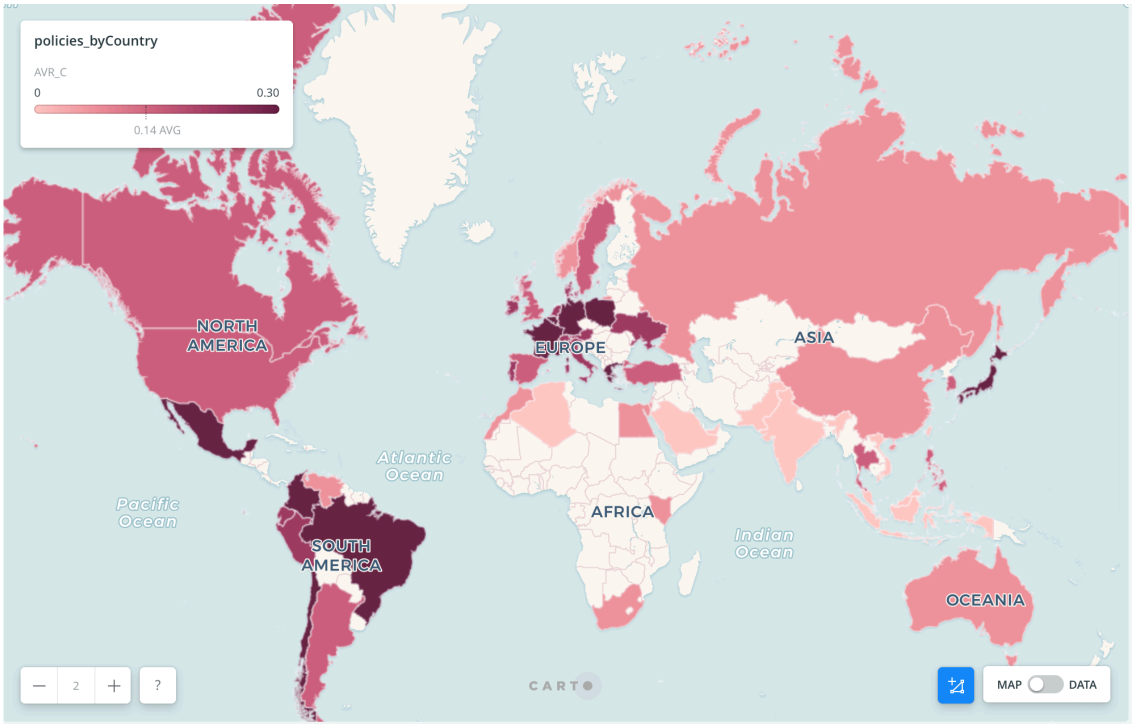
(a) Build additional roads



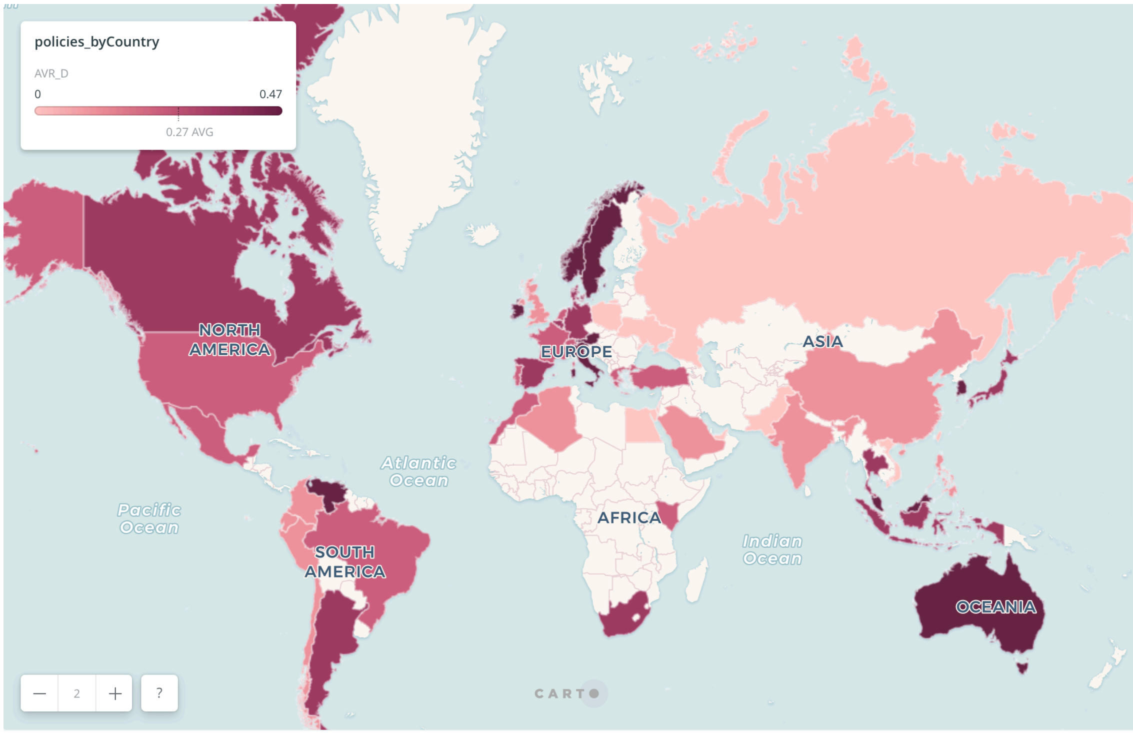
(b) Discourage the use of private automobiles in the city center



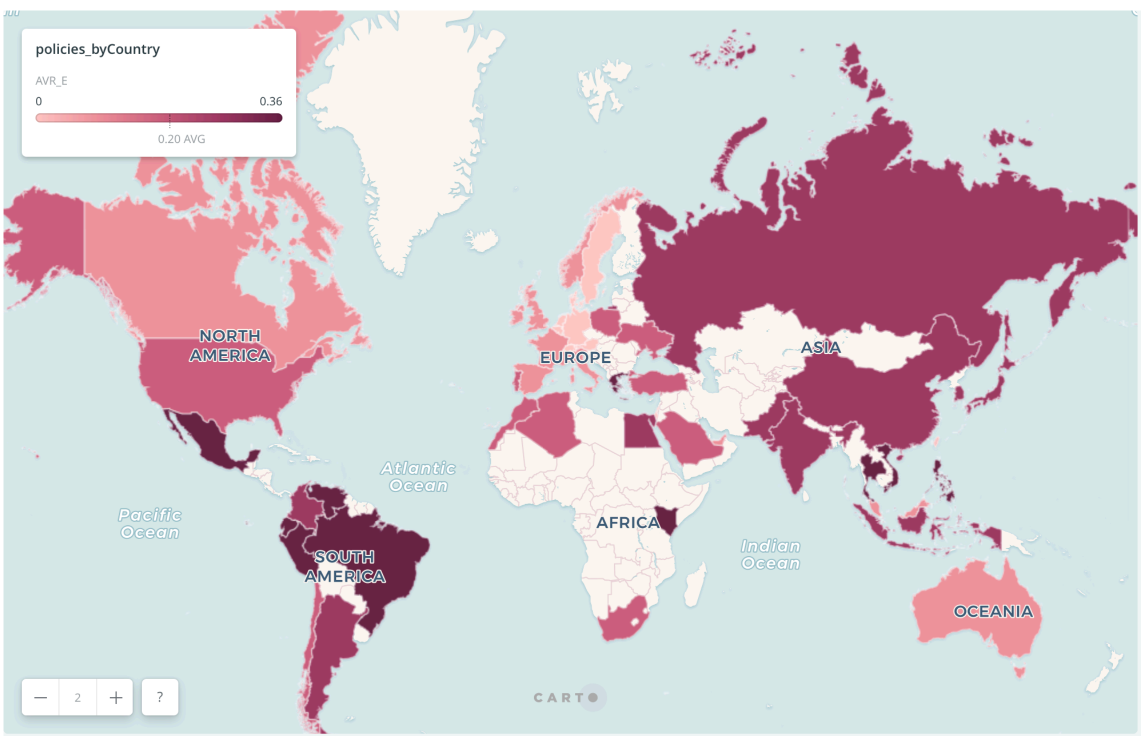
(c) Expand bike lanes



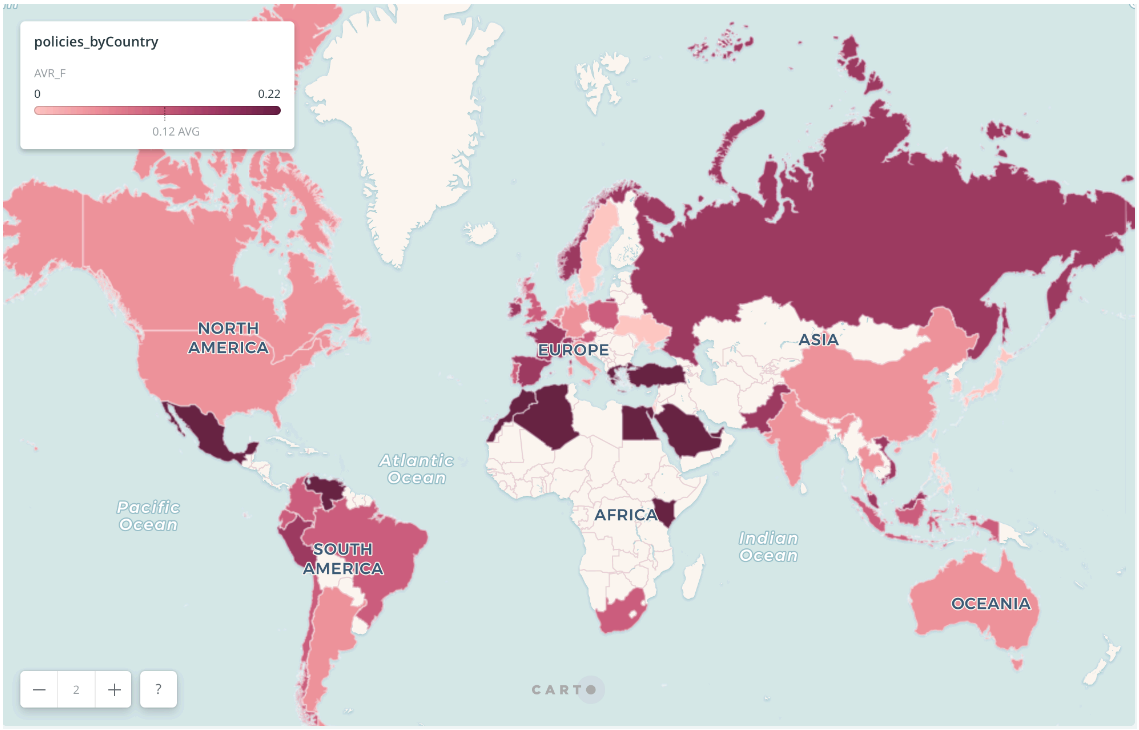
(d) Expand public transportation services (bus/train)



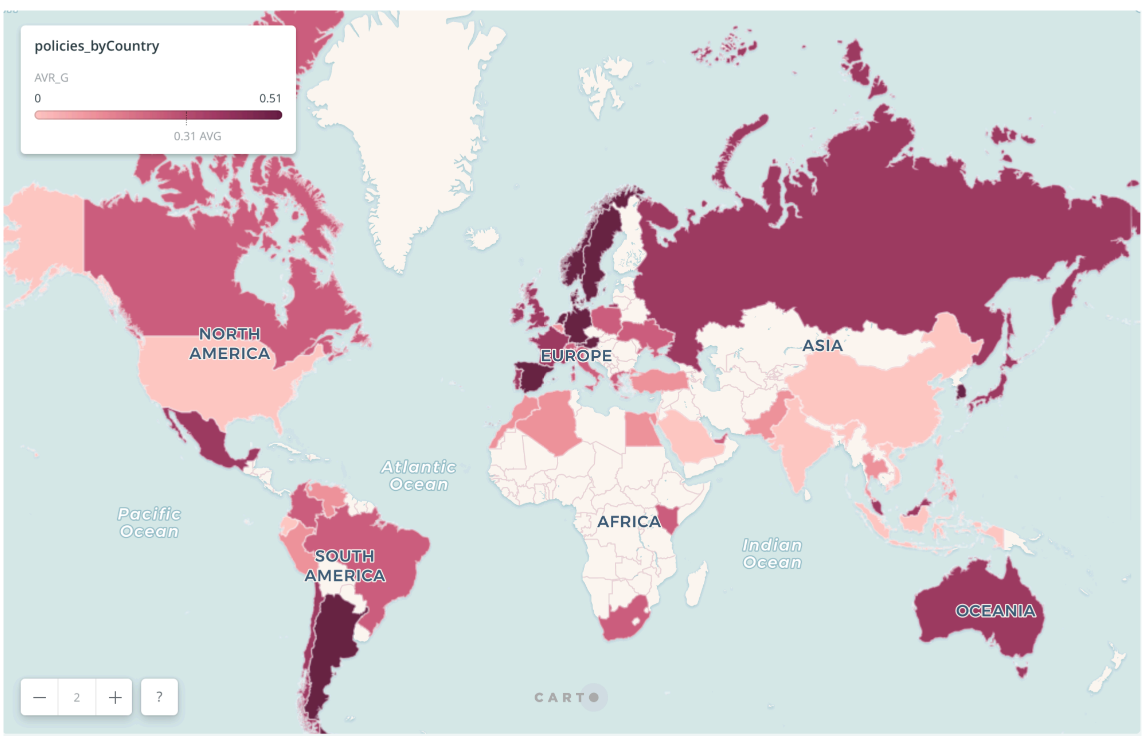
(e) Improve pedestrian facilities (sidewalks, street crossings, etc.)



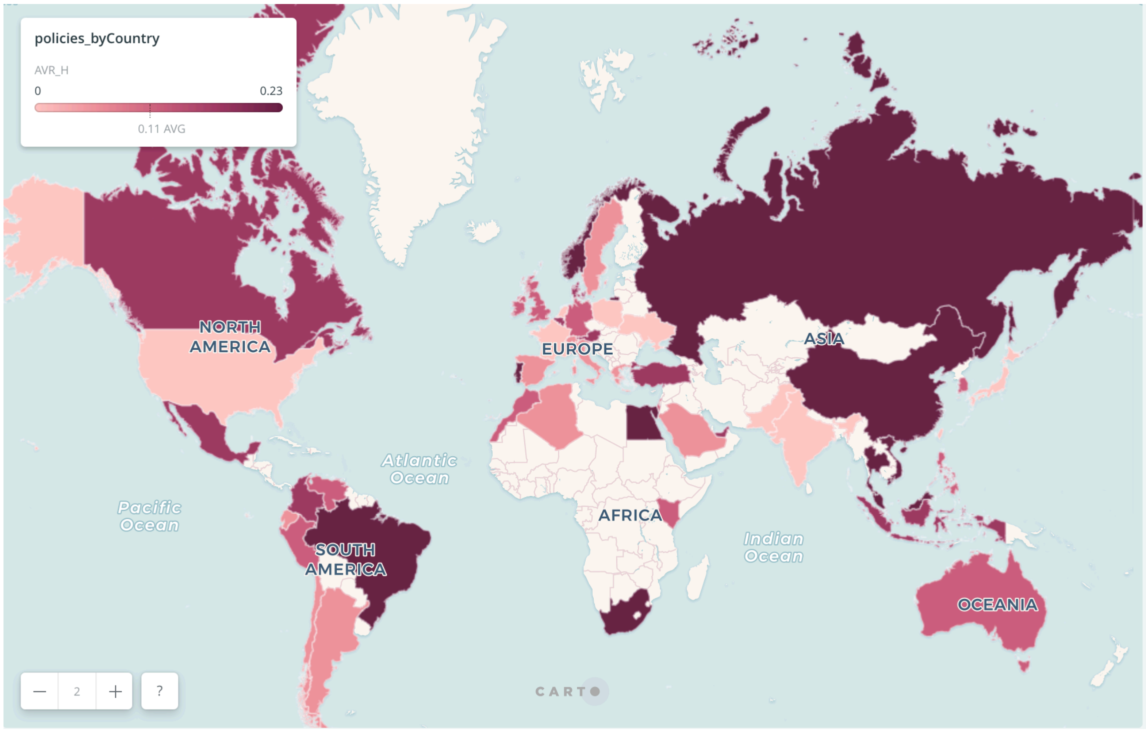
(f) Introduce car-free pedestrian zones in the city center



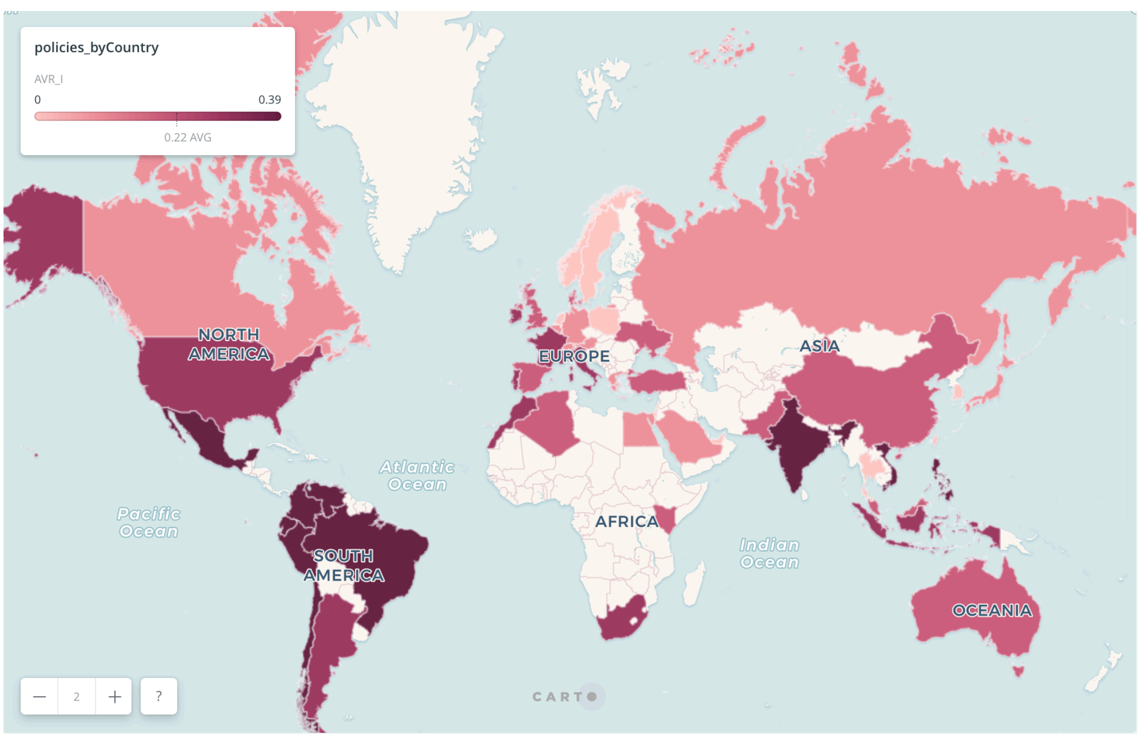
(g) Lower public transportation fares



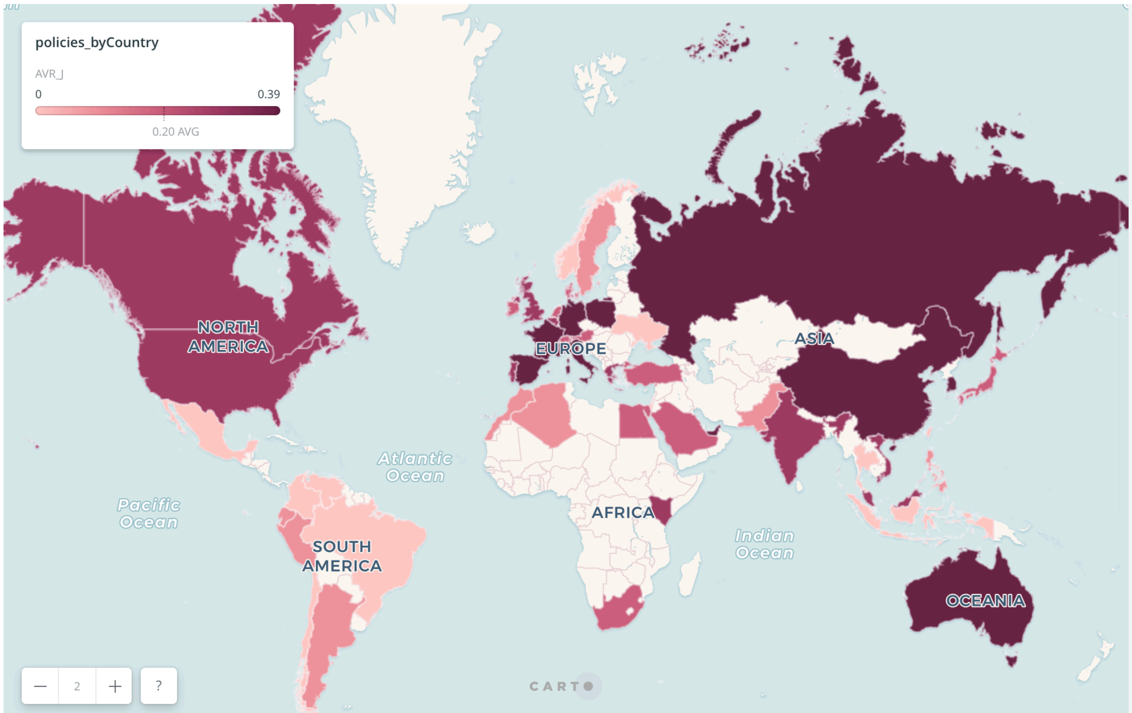
(h) Prioritize public bus lanes and/or bus rapid transit



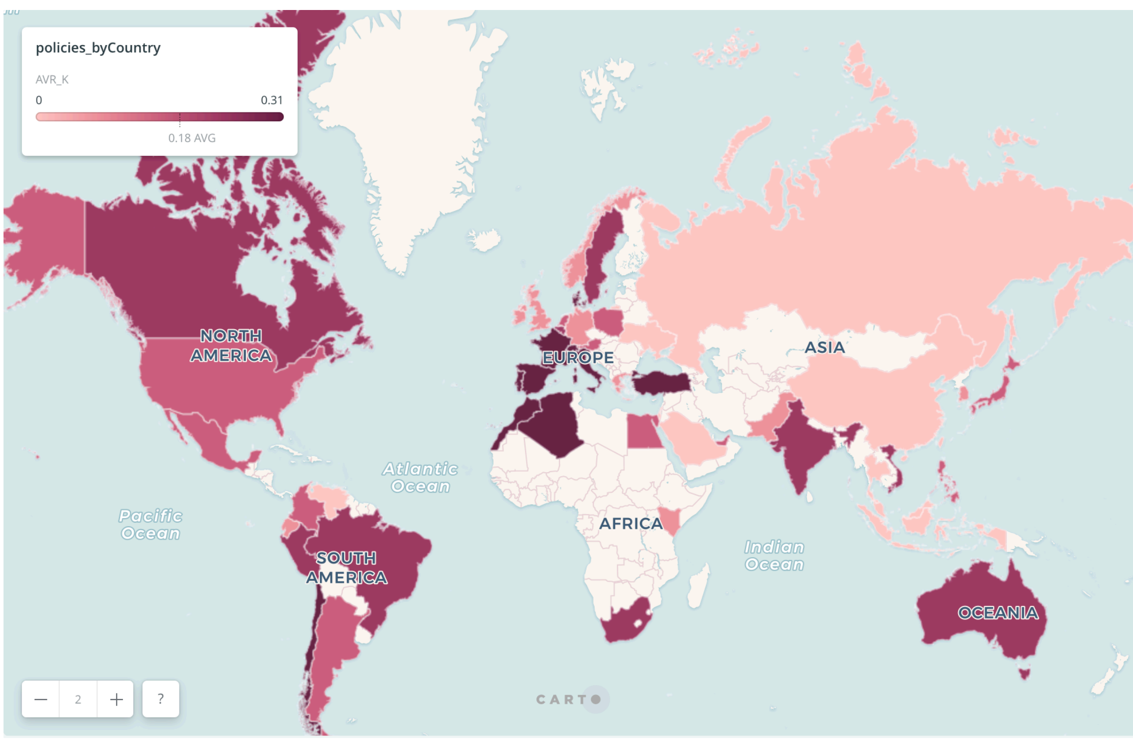
(i) Provide clean energy-based public transportation options



(j) Provide more parking spaces



(k) Subsidize clean energy vehicles



3.3 Dataset Hierarchical Structure

By following the description of the sampling techniques, readers may have noticed the hierarchical structure of the data: individuals are nested within countries. Again, the data is collected by sampling individuals within countries to be representative of each country's population by age and gender. This complicates the investigation of factors that affect different policy support, as there are two types of variances: first, as individuals of different socio-demographic characteristics and travel behaviors, survey respondents have different mobility experiences and therefore different support/prioritization on policy items. Second, people residing in the same country may share similar characteristics, for example, similar mindset on transportation options, due to the influence from the national context. From the figure above, we can discern that countries follow different patterns in prioritizing transportation policies, but we need to differentiate if the differences we see across countries are due to the fact that different types of people live in different countries, or if there is hypothesized country-level effect. Therefore, I used the intra-class correlations (ICC) to examine if the ratio of variance at the country level to total variance is significant. The results after using R package "glmer" are in Table 3.2. Note that, country-level variance only counts for a small portion (about 2%-6%) of the total variance. All country-level variances are significant, probably due to the large individual sample size.

Table 3.2 The country-level ICC for 11 policies.

Index	Policy	ICC
A	Build additional roads	0.068***
B	Discourage the use of private automobiles in the city center	0.067***
C	Expand bike lanes	0.056***
D	Expand public transportation services (bus/train)	0.034***
E	Improve pedestrian facilities (sidewalks, street crossings etc.)	0.047***
F	Introduce car-free pedestrian zones in the city center	0.031***
G	Lower public transportation fares	0.063***
H	Prioritize public bus lanes and/or bus rapid transit	0.027***
I	Provide clean energy-based public transportation options	0.044***
J	Provide more parking spaces	0.054***
K	Subsidize clean energy vehicles	0.029***

Significance code: * = 10%, ** = 5%, *** = 1%

To explain the ICC results, for example, about 6.8% of the variances of policy support of building additional roads come from individuals being in different countries. That means, individuals' difference can account for about 93.2% of total variances. Across all ICCs, the percentages range from 2.7% to 6.8%. The use of ICC confirms that country variance exists; only addressing individual level variance will eliminate interesting dimension from the global scale the data enables. So I will separate the variation in the data attributable to individuals and the variation in the data attributable to countries. A model to address multilevel varainces is therefore needed.

3.4 Latent Variable

Car pride is a variable that captures the emotion attached to cars. For example, one can think of cars being luxury good and being able to drive/own a car represents an extraordinary social symbol. I suspect that the attitude toward cars, one strong alternative against other modes, would lead to policy preferences that aim at in particular "car-oriented" end goals. This car pride variable can be measured by a series of indicators designed to cover aspects of a person's positive or negative attitudes on owning and using cars. The 9 indicators designed for car pride in the survey can be found in Table 3.3.

Table 3.3 9 indicators of car pride (used in measurement model)

Index	Indicators of Car Pride
Indicator 4A	A car is a sign of social status
Indicator 4B	Driving meets my self-esteem or personal image
Indicator 4F	I gain respect from my peers because I drive a car
Indicator 4K	If more people saw me in/with my car, I would drive more
Indicator 5A	Having a car is connected with my social image
Indicator 5B	I feel proud of owning a car
Indicator 5C	I have a sense of accomplishment after buying a car
Indicator 5D	I have achieved in life and therefore I deserve to own a good car
Indicator 5F	Others would see me as more successful if I owned a better car or more cars

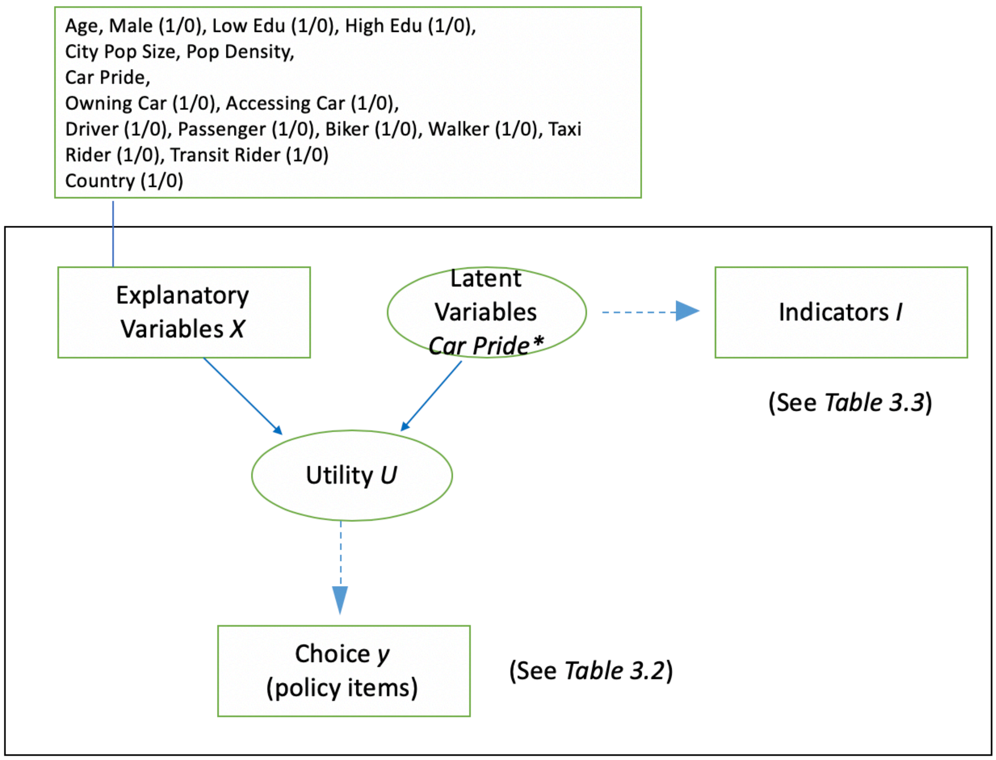
The availability and usefulness of car pride, the latent variable, makes the analysis interesting. A model has to take latent variable into consideration.

3.5 Discrete Choice Modeling with Latent Variable/ Structural Equation Model

3.5.1 Assumptions

The simultaneous Structural Equation Model (SEM) or hybrid discrete choice model contains one set of equation models and one set of measurement models. The measurement model of SEM is used to measure unobserved latent variables from a series of indicators designed to capture such latent variable in the survey, using confirmatory factor analysis. The equation model is an extension of multiple regressions, taking in observed variables like gender, age, income, etc. onto the utility function, but also allows the interaction of observed variables with latent variables. Figure 3.3 better present the relationship. Error terms are assumed to follow the standard logistic distribution.

Figure 3.3 Model structure of explanatory, dependent, lantent variables and indicators.



3.5.2 Analysis for Multilevel Structure

The modeling should recognize country/cluster effects of the data for two reasons. First, the data is designed to include latent variables and has a series of indicators for the latent variable—car pride. Figure 3.3 shows the individual-level SEM structure of explanatory, dependent, latent variables and indicators. Second, I recognized the nested structure of the data. The data is collected by sampling individuals within countries to be representative of each country's population by age and gender; the intra-class correlations (ICC) confirm that the country level variance of the total response variance in support of the 11 different policies is significant, though small.

The next task is to find an appropriate model to address the cluster effect. There are two approaches valid and commonly used to address the cluster effect. One approach is multi-level structural equation model; the other approach is using single-level SEM, but incorporating other variables that control for cluster effects to further explain observed variance. I am going to discuss how to choose from the two methods based on ICCs and group level sample size. Hox (2013) explains that the multi-level SEM assumes sampling at the individual and the group level, with both within group (individual level) and between-group (group level) variance and covariance. This approach is beneficial in a way that the latent variable is estimated at both individual and group level; the utility function therefore, is influenced by both individual variables as well as group-level variables. However, Hox notes that, if ICCs of the variables are smaller than 0.05, the between-group variance is small and there may be no need for a complex group-level modeling. The reason comes from essentially more interactions in multi-level modeling and thus more parameters to estimate when we consider clusters. For regular multi-level regression, Eliason (1993) recommends a minimum sample size of 60 when maximum likelihood estimation is used; in multi-level modeling, this applies to the highest level. But a sample size for the highest level can be as low as 20, if our interest is in estimating the coefficients of group-level variables and their standard errors (Maas and Hox 2005). When it comes to multi-level SEM, it fundamentally bases on the within-group and between-group covariance matrices; hence, the recommendation for the accurate estimation of higher level variances in multilevel regression carries over to SEM: at least 100 groups are recommended, but in small models 50 groups may suffice (Hox, Maas and Brinkhuis, 2010).

This study is mainly interested in individual-level variances and extensions on the single-level SEM can suffice in controlling for country-level variances due to the small ICC. But if the researcher is fundamentally interested in the multi-level structure and if the ICC is large, then he/she should think of deploying multi-level modelling or multi-level SEM.

We therefore introduced country dummies to the modeling. For example, there are 52 countries/regions in the dataset so that there will be (number of countries -1) dummies presenting if the person is in China (yes or no), in the U.S. (yes or no), in Egypt (yes or no), etc. The advantage of using the country dummies is that the coefficients estimated for each country forms ranking. This information *per se* is useful for us to get a sense of the degree of being in one country affects the person's support toward certain policies. Formulas below better illustrate my ideas:

$$Support_{ijk} = f\ (\ Age_{ij}, Male_{ij}, Low\ Edu_{ij}, High\ Edu_{ij}, Income_{ij},$$

$$City\ Pop\ Size_{ij}, Pop\ Density_{ij},$$

$$Car\ Pride_{ij},$$

$$Owning\ Car_{ij}, Accessing\ Car_{ij},$$

$$Driver_{ij}, Passenger_{ij}, Biker_{ij},\ Walker_{ij},\ Taxi\ Rider_{ij}, Transit\ Rider_{ij},$$

$$country\_FE_{ijk})$$

where *i* represent individual, *j* represents policy item and *k* represents country; *country_FE* is the country fixed effect, meaning whether a person is being in one country or not. Note that Taiwan does not have statistics published on the World Bank dataset; for the consideration of legitimacy of the data comprehension, I did not include Taiwan in the final dataset. Therefore, I dropped 1,040 individuals from Taiwan and the final data size is 41,932.

Since we have 51 countries/regions, there are 50 coefficients to be estimated. The 50 country dummies can form country ranking on particular policies. South Africa has been dropped due to the alphabetical order (country code: ZA). The explanation of country dummy estimates could be that, after controlling all individual characteristics, like age, gender, income, etc. the effect of being in one country on the policy support. The reader can think about, for example, one individual being female, college education, age 25; if the person resides in Australia vs. in Morocco, the same person's support on policy, like expanding transit services, would possibly be different. The variance due to different countries is what country dummies try to capture. The analysis of country-level difference on different policy support will be covered in Chapter 5.

Furthermore, some of the country-level variables like GDP, GINI, population density and urbanization rate can be higher-level variables that correlate with policy support. Scatter plots can be used to show the relationship between policy support and country's GDP per capita or urbanization rate. The color coding for developing or developed status should be used for distinguishing the two types of countries.

3.5.3 Separate Models and Choice Combination

One more problem in modeling is that there are 11 separate models, one for each policy item. Comparing 11 models is not easy and sometimes involves many back-and-forth processes. Note that since people are allowed to choose up to three policy items, the 1s here only represent having the policy as one of the top three that a person would prioritize. The framing may be different from traditional discrete choice modeling where people are allowed to choose only one alternative. There are possible ways to address the choice constraint and some of ideas will be discussed later. But to account for the policy interpretation, for now the main modeling will keep the structure of 11 separate models.

To visually and intuitively understand the landscape of 11 policies, we tried the technique called principal component analysis (PCA) and found that some policies were more likely to be chosen together, according to Figure 3.4. PCA is the technique to find out the components that explain the most variances in the dataset and project the dataset onto those dimensions. Typically, we would use 2 most important components—principal component 1 (PC1) and principal component 2 (PC2) that explain most of the data variance to visualize the data in lower dimensions, for example, in a 2D plot. From Figure 3.4, arrows of building additional roads and providing more parking spaces are closer and point to similar directions, which means those two were always chosen together in the data. I would like to call these two "pro-car policies". Expanding public transportation public transportation services (bus/train), prioritize public bus lanes and lower public transportation fares can be grouped together as pro-transit policies. All the rest would be grouped together; there is no coherent name to call them, but they represent sustainable/fairly new and active mobility alternatives. The 3 colors indicate 3 clusters given by k-means; 3 is the optimal number of clusters by the elbow method, shown in Figure 3.5. More discussion on clustering techniques will be covered in Chapter 5.3.1. Having clusters on top of the PCA helps readers visualize how data are distributed in 11 dimensions (11 policies) and thus find patterns.

Figure 3.4 PCA of 11 policies by support (0 or 1) of all individuals.

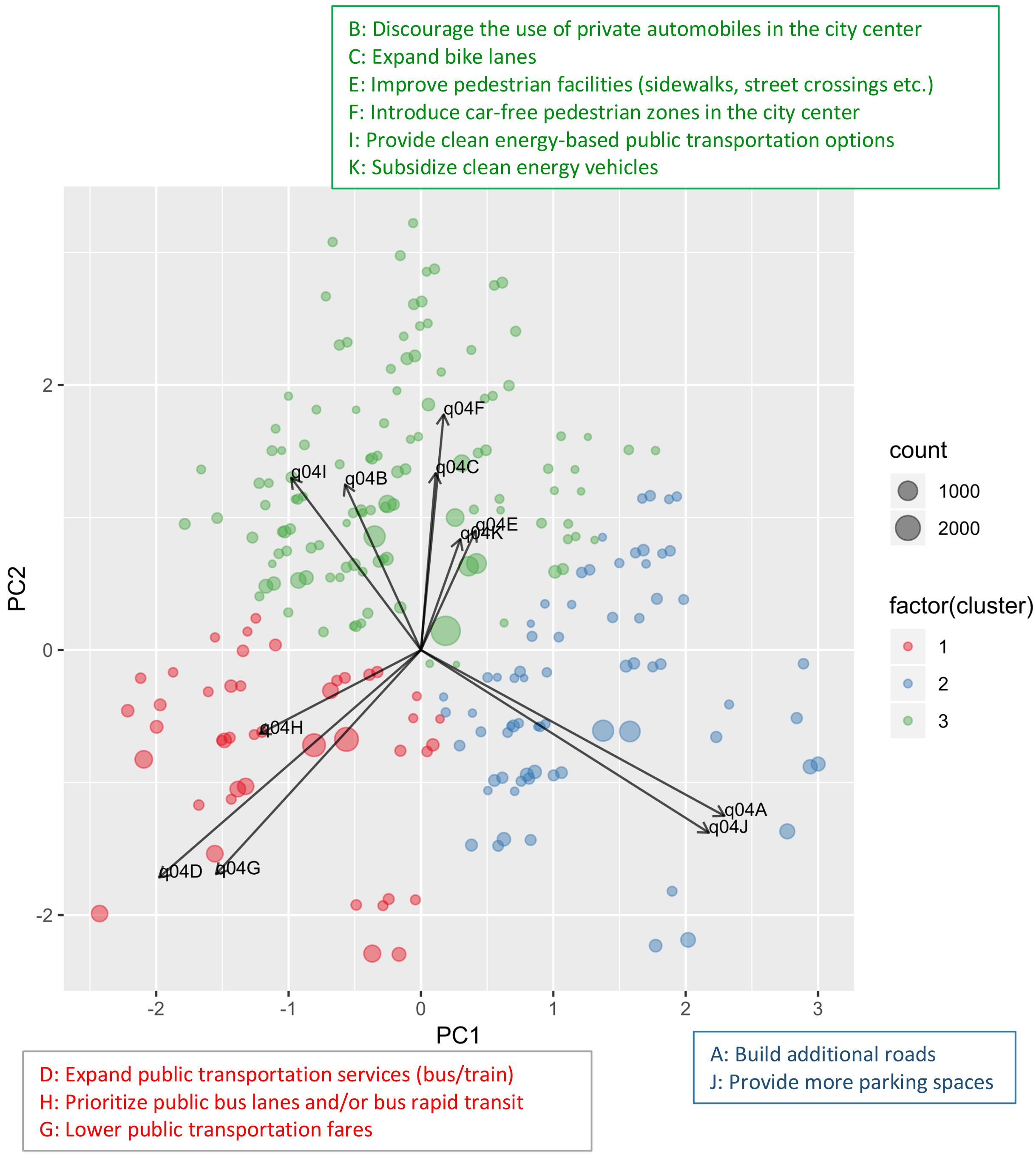
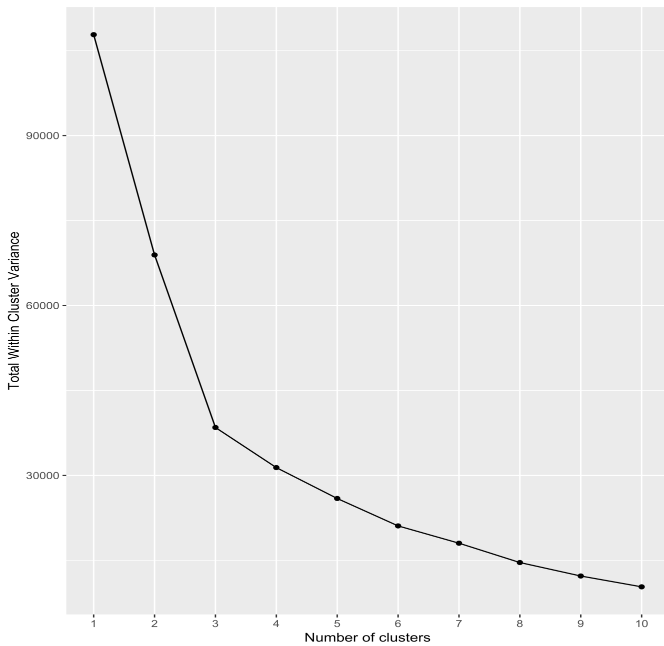


Figure 3.5 Elbow method to determine the optimal number of clusters. 3 is the optimal.



Grouping policies reduces the number of models to run, but results in ambiguity in terms of result interpretation. If we think of the model estimate in terms of how much percentage change in explanatory variables affect policy support, when we have single policy as the dependent variable, it is straightforward to understand the effects of age, gender, income, etc. on the single policy support. But if it comes to a combo of two, three, or four policies, the interpretation becomes less straightforward. We will obtain estimations like x percentage change in income affecting x percentage change in pro-car policies. But it lacks direct policy implication as the interpretation becomes vague and complicated. I would acknowledge the limitation of running 11 models separately upfront, but it is a good method to keep the originality of the policy interpretation. In the chapters later, the pro-car, pro-transit groups from PCA are mainly used to organize and present the results in a clearly readable way.

Another way to address the "up-to-three" constraint in the utility maximization function is to list out all the possible combinations and treat each possible combination as an outcome. The number of unique combinations of up-to-3 policies out of 11 is 232 (people can choose 0, 1, 2, or 3 policy items). One can think of the modelling approach as multi-nominal logit and each unique policy combination is one alternative in the choice set. This approach of maximum utility estimation with more-than-one choices has been applied by Viegas de Lima, et.al. (2018) in their day travel pattern study in the Greater Boston Area. This method will be explained more in

Chapter 6. But the major model of this thesis (Chapter 3 and 4) will deploy the 11 separate models.

3.6 Model Specification

The final model I propose here can count for both individual and country level variances. The model is single-level discrete choice modeling with latent variables and standard cluster (country) standard errors. The way to specify in Mplus is having "TYPE == COMPLEX" in the ANALYSIS section. The estimation method is maximum likelihood estimation ("ESTIMATOR = MLR") and integration is Monte Carlo ("INTEGRATION = MONTECARLO").

By specifying ESTIMATOR=MLR, a maximum likelihood estimator with robust standard errors, normally using a numerical integration algorithm will be used. Monte Carlo simulation is used here because numerical integration becomes increasingly more computationally demanding as the number of mediating variables with missing data and the sample size increase. (Muthén & Muthén, 1998-2019*)*. In my example, Monte Carlo integration with 500 integration points is used.

There is no missing value on the dependent variables; the missing independent (predictor) variables like income are handled by full information maximum likelihood techniques, which assume missingness at random.

Final variables included in Mplus are :

The measurement model of car pride takes 9 indicators and fixes the variance of car pride to 1.

The equation model, for example, the model for supporting building more roads looks like:

$$More\ Road_i = f\ (\ Age_i, Male_i, Low\ Edu_i, High\ Edu_i, Income_i,$$

$$City\ Pop\ Size_i, Pop\ Density_i,$$

$$Car\ Pride_i,$$

$$Owning\ Car_i, Accessing\ Car_i,$$

$$Driver_i, Passenger_i, Biker_i,\ Walker_i,\ Taxi\ Rider_i, Transit\ Rider_i,$$

$$country\_FE_i)$$

i means individuals. $country\_FE_i$ contains 50 binary variables. Since we have 51 countries/regions, there are 50 coefficients to be estimated. South Africa has been dropped out because it is the last one by the alphabetical order of the country code. The remaining country codes are:

$country\_FE_i$ = {AE AR AT AU BE BH BR CA CH CL CN CO DE DK DZ EC EG ES FR GB GR HK ID IE IL IN IT JP KE KR MA MX MY NL NO PE PH PK PL PT RU SA SE SG TH TR UA US VE VN}

More details of the variables are explained in the following:

Age means the age of the person at the year of 2017.

Gender is 1 if the person is male and 0 if the person is female.

Education has categories from low, medium, high and no answer. Binary variables indicating low education an high education were constructed.

Income was designed as bracket in the original survey. People were asked to choose the income bracket if his/her household's monthly income after taxes in local currencies falls in that bracket. The income brackets range from under $250, 250-500, 500-1000, 1000-2000, 2000-3000, 3000-4000, 4000-6000, 6000-8000, 8000-10000, 10000-12000, 12000-15000, more than 15000 and prefer not to say. The income is then modified in a way that we used the midpoint in a given range and treated the income variable as a continuous variable. If the income is more than 15000, then we chose 17500 for this range since 17500 seems like a reasonable value based on the income histogram. The income variable was log-transformed due to its skew distribution across individuals.

City Pop Size is the allocation (city/township) size variable, which measures how many people are at the respondent's city/village. The options include 'Town with fewer than 1000 people', 'Town with 1,000 - 50 000 people', 'City with 50 000 - 250 000 people', 'City with 250 000 - 1 million people', 'City with 1 million - 5 million people', 'City with 5 million - 10 million people', 'City with more than 10 million people'. Similar to the income variable, I transformed the city size variable by using the average of the range; therefore, the values of the city size variable are 250, 500, 25500, 150000, 612500, 3000000, 7500000, 12000000. This is a self-reporting variable; so, the reality (the actual size of the city/village/township where people reside) may be different from people's perception. But the perception of the size of the living place could also reflect on people's policy support choices. This variable has been log-transformed as well.

Pop Density means population density at each respondent's recorded GPS. This information was extracted from European Commission Global Human Settlement Layer (GHSL) global layer at 1 km in 2015 (European Commission, 2015). The value means the number of people per 1 km raster cell. I included this variable because one hypothesis is that people living in rural areas or areas with low density may have no public transportation option in mind. An objective measurement here would help test if the density of living places would affect people's mindset of transportation policies. But this variable has limitations. First, people could have taken the survey in places different from the "place" they have in mind to answer for. A simple example is that people may refer to the city/town where they work at in the question city population size (the location size question). But they may reside in suburbs and take the survey at home, so the GPS recorded is at the suburb and thus has low density compared to the place they have in mind. Second, there are some empty cells in the raster layer, possibly due to limited satellite coverage, which can obscure findings.

Finally, Driver, Passenger, Biker, Walker, Taxi Rider and Transit Rider indicate primary commuting modes. Rail rider refers to taking train, underground/metro/subway and tram as the primary commuting mode. Categories like Transit rider and Other are thus combinations of a few. The statistics of the commuting mode variables is shown in Table 3.4.

Table 3.4 Statistics of travel mode variables. Categories like Transit rider and Other are combinations of a few.

Variable	**Description**	**Number of sample**
Biker	**Bicycle**	**4086**
Bus	**Bus/minibus**	**10581**
Driver	**Car: driver**	**17887**
Passenger	**Car: passenger**	**9721**
Taxi rider	**Taxi or other hired vehicle**	**3937**
Transit rider	**Rail transit**	**9011**
	Train	3363
	Underground/Metro/Subway	4138
	Tram	1510
Walker	**Walking**	**6666**

Other	**Other** (reference category)	**9346**
	Boat/ferry	360
	Rickshaw	442
	Other Public Transport	2584
	Other Private Vehicle	1429
	Electric bicycle	755
	Motorbike/scooter	3776

Next, in Chapter 4, we will provide result analyses from the model above and focus on the individual level. The results shed lights on individual socio-demographics, location characteristics, car pride and travel modes. In Chapter 5, we will discuss country dummies and provide result analysis on the country level.

4 Policy Support and Individual-level Analysis

This chapter discusses how individual characteristics predict individual's support of different transportation policies. In chapter 2, we have discussed that how previous studies have shown that demographics, location characteristics and travel mode significantly correlate with the public support of policies. To remind readers, we summarized findings that first in terms of socio-demographics, **older** people are more opposite to job-housing balancing policy proposals, more opposite to ridesharing (Baldassare, 1991) and people younger than 44 years old are less likely to accept congestion pricing (Rentziou et al., 2001). Kim et al. found that **females** are more difficult to accept road pricing (2013). **High household income** is significant in predicting opposition to parking fees to encourage carpooling and to job-housing balance proposal (Baldassare, 1991). **High-education** respondents are more likely to accept congestion pricing (Rentziou et al., 2001). Second, in terms of location characteristics, residents of smaller towns tend to accept pricing more easily (Vrtic et. al., 2007) and respondents who traveled to the pricing area by taxi were more likely to accept congestion pricing (Rentziou et al., 2011). Lastly, *per* travel mode, respondents who traveled by car or by motorcycle were less likely to accept congestion pricing (Rentziou et al., 2011)

Because the previous literature concentrates on road pricing and congestion charging mainly, those results are not entirely comparable to the model results of 11 polices in this thesis. However, similar analyses can be done in the sequence of demographics, location characteristics, travel mode and car pride which is new in our study, to present the significant factors that contribute to support of each of the 11 policies in our survey.

4.1 Model Results

For ease of legibility, we break the results of the 11 model runs into three tables, one for pro-car policies (Table 4.1), one for pro-transit policies (Table 4.2), one for clean-energy policies (Table 4.3) and one for all other policies (Table 4.4).

Table 4.1 Model result for pro-car policies.

Variable	**Build roads**	**More parking**
Individual socio-demographics		
Age (years)	-0.002**	0.000
Male (0/1)	0.136***	-0.086***
Low education (0/1)	0.016	0.001
High education (0/1)	0.018	-0.003
Monthly household income (local $)	0.018*	0.009

Has access to car (0/1)	0.085***	0.213***
Owns car (0/1)	0.130***	0.292***
Location characteristics		
City size by its population	0.002	0.023***
Population density of response location (ppl/km^2)	0.000	0.000
Attitudes		
Car pride	0.233***	0.220***
Commuting mode		
Car: driver (0/1)	0.166***	0.167***
Car: passenger (0/1)	0.082***	0.089***
Bike (0/1)	-0.065*	-0.115***
Taxi (0/1)	0.041	0.092***
Walk (0/1)	-0.066***	-0.023
Rail (0/1)	-0.076***	-0.058***
Goodness of Fit		
Akaike (AIC)	406910.175	412699.017
Bayesian (BIC)	407670.165	413459.672
Sample-Size Adjusted BIC	407391.165	413180.008

Notes: standardized regression coefficients by STDY in Mplus;
p-value of two-tailed t-test against b = 0: * < 0.1, ** < .05, *** < .01

Table 4.2 Model result for pro-transit policies.

Variable	**More PT**	**BRT**	**Lower PT Fare**
Individual socio-demographics			
Age (years)	0.003***	-0.001	0.001*
Male (0/1)	-0.085***	0.037*	-0.172***
Low education (0/1)	-0.087***	-0.052*	-0.06***
High education (0/1)	0.128***	0.078***	-0.008
Monthly household income (local $)	0.035***	0.028**	-0.026**
Has access to car (0/1)	0.006	0.014	-0.043*
Owns car (0/1)	-0.038	-0.068**	-0.038**
Location characteristics			
City size by its population	0.005	0.015***	0.014***

Population density of response location (ppl/km^2)	0.002	0.002	0.003*
Attitudes			
Car Pride	-0.055***	0.075***	0.025*
Commuting Mode			
Car: driver (0/1)	0.063***	-0.049*	-0.041*
Car: passenger (0/1)	0.032*	-0.007	0.001
Bike (0/1)	-0.093***	-0.016	-0.078***
Taxi (0/1)	0.06**	0.1***	0.029
Walk (0/1)	0.052***	0.035	0.102***
Rail (0/1)	0.222***	0.224***	0.229***
Goodness of Fit			
Akaike (AIC)	420134.988	400424.676	422194.719
Bayesian (BIC)	420895.642	401185.331	422955.374
Sample-Size Adjusted BIC	420615.978	400905.666	422675.710

Notes: standardized regression coefficients by STDY in Mplus;
p-value of two-tailed t-test against b = 0: * < 0.1, ** < .05, *** < .01

Table 4.3 Model result of clean-energy polices.

Variable	**Clean PT**	**Clean Cars**
Individual socio-demographics		
Age (years)	0	0.004***
Male (0/1)	-0.041**	0.054***
Low education (0/1)	-0.045**	-0.075***
High education (0/1)	0.06***	0.048***
Monthly household income (local $)	0.047***	0.055***
Has access to car (0/1)	0.025	0.093***
Owns car (0/1)	-0.011	0.142***
Location characteristics		
City size by its population	0.008***	0.005
Population density of response location (ppl/km^2)	-0.003	-0.004*
Attitudes		
Car pride	0.04***	0.1***
Commuting mode		
Car: driver (0/1)	-0.027	0.1***
Car: passenger (0/1)	0.031**	0.073***

Bike (0/1)	-0.013	-0.003
Taxi (0/1)	0.1***	0.101***
Walk (0/1)	0.068***	0.098***
Rail (0/1)	0.092***	0.012
Goodness of Fit		
Akaike (AIC)	422675.710	410594.023
Bayesian (BIC)	415086.556	411354.678
Sample-Size Adjusted BIC	414806.891	411075.013

Notes: standardized regression coefficients by STDY in Mplus;
p-value of two-tailed t-test against b = 0: * < 0.1, ** < .05, *** < .01

Table 4.4 Model result for all other policies.

Variable	**Car-light CBD**	**Bike Lanes**	**Pedestrian Facilities**	**Car-free Ped CBD**
Individual socio-demographics				
Age (years)	0.008***	-0.001	-0.004***	0.002*
Male (0/1)	0.121***	0.02	-0.143***	0.016
Low education (0/1)	-0.061**	0.019	0.012	0.015
High education (0/1)	0.069***	0.074***	0.013	0.062***
Monthly household income (local $)	0.021**	0.013	0.009	0.015
Has access to car (0/1)	0.048	0.007	-0.053**	0.021
Owns car (0/1)	0.015	0.034	-0.077***	-0.053
Location characteristics				
City size by its population	0.016***	0.006**	0.003	0.006
Population density of response location (ppl/km^2)	-0.003	-0.005	0	0
Attitudes				
Car Pride	0.061***	-0.01	0.078***	0.112***
Commuting Mode				
Car: driver (0/1)	-0.051**	-0.058***	-0.02	-0.019
Car: passenger (0/1)	-0.02	-0.018	0.068***	0.068***

Bike (0/1)	0.119***	0.53***	0.014	0.116***
Taxi (0/1)	0.056*	-0.012	0.063***	0.031
Walk (0/1)	0.058*	0.111***	0.154***	0.134***
Rail (0/1)	0.091***	-0.048**	-0.018	0.007
Goodness of Fit				
Akaike (AIC)	397021.194	405080.492	412387.226	400928.856
Bayesian (BIC)	397781.849	405841.146	413147.880	401689.511
Sample-Size Adjusted BIC	397502.185	405561.482	412868.216	401409.846

Notes: standardized regression coefficients by STDY in Mplus;
p-value of two-tailed t-test against b = 0: * < 0.1, ** < .05, *** < .01

4.1.1 Individual Socio-demographics

First, we consider the effect of individual sociodemographic characteristics—like income, education level, age, and car ownership and access—on support for each of 11 transportation policies. We find that household income does not distinguish support on road/parking policies; but higher income is correlated with expanding transit, prioritizing transit, subsidizing new energy transit and vehicles. There are some counterintuitive results. For example, we may suspect that people with high income would tend to use cars more and thus have less support on transit related policies. But the results show that people with higher income tend to support expanding transit services and prioritizing bus lane/BRT. Also, people with higher income tend to support discouraging car use in the center city. But the same time, they also support clean energy vehicles and clean energy transit. The only significantly negative coefficient of income is for the lowering transit fare item. This one makes sense as higher income people are less sensitive to transit fares and would not choose lowering transit fares as the policy item of priority.

High education people and low education people behave differently on supporting expanding transit, prioritizing transit, discouraging car use in center city, subsidizing clean energy transit/vehicles. High education and higher income groups behave somehow similar on many of the policies. For example, those two groups both support expanding public transportation, prioritizing public bus lanes and/or BRT, discouraging the use of private automobiles in the city center, subsidizing clean energy vehicles and providing clean energy-based public transportation services.

In terms of age, being older leads to less support on building more roads and improving pedestrian facilities (sidewalks, street crossing, etc.). While older people also support discouraging the use of private automobiles in the city center and introducing car-free pedestrian zones in the city center.

Next, owning and having access to a car show similar patterns in terms of support for roads, parking, and clean energy vehicles. But car ownership has a stronger impact than car access on many policy support items; for example, owning a car leads to more opposition to transit and pedestrian facility policies.

4.1.2 Location Characteristics

Individuals living in cities or towns with larger population size tend to support more parking, prioritizing bus lane/BRT, lower transit fares, discouraging car use in city center and providing clean energy public transit services.

4.1.3 Car Pride

Next, we consider the impact of an individual's car pride on their policy support. We find that car pride is significantly predictive of support of many transportation policies. In particular, higher car pride is predictive of greater support on many policies. Car pride is significantly positive on building additional roads and providing more parking spaces. Higher car pride leads to less support on expanding transit, which makes sense. But meanwhile, car pride is positive on prioritizing transit, lowering transit fares, discouraging the use of private automobiles in the city center, and introducing car-free pedestrian zones in the city center, which are the policies that impose restrictions on car use. However, it is negatively predictive of support of public transit service expansion.

One possible explanation is that though people are proud of owning/using their cars, they realize that the city needs something more than the facilities that fulfill their own preference. Or, possibly, people with higher car pride are not necessarily the actual car owners or car users. They have higher car pride because they cannot own it. Those people may use alternative modes and thus like to support policies that improve conditions of what they actually use. More research has to be done on the relationship.

4.1.4 Commuting Mode

If we compare the parameters vertically, i.e. within one policy, for the policy regarding building more roads and parking, people who bike, walk or take transit as primary mode are less likely to support it. Current users of the mode (e.g., bikers, drivers, passengers) have large influence on policy support, by comparing parameters' magnitudes.

The primary commuting mode variables are worthwhile to dig into more. Bike and transit seem to be competing against each other. Bikers support less on transit policies and transit riders less support on expanding bike lanes. Ideally, bikes can be first/last-mile tools that connect with subways or metro. But the current circumstance is that the two may have conflicts, probably in road space or funding, thus leading to competition for public resources.

4.2 Discussion by Audiences

Many of the results have implications to policy making and research. Many of the variables and associated policy influences are studied by institutes, organizations and government; examples will be given in the following sections. With the scope of 11 policies, a detailed interpretation of model results may cater the need of many audiences.

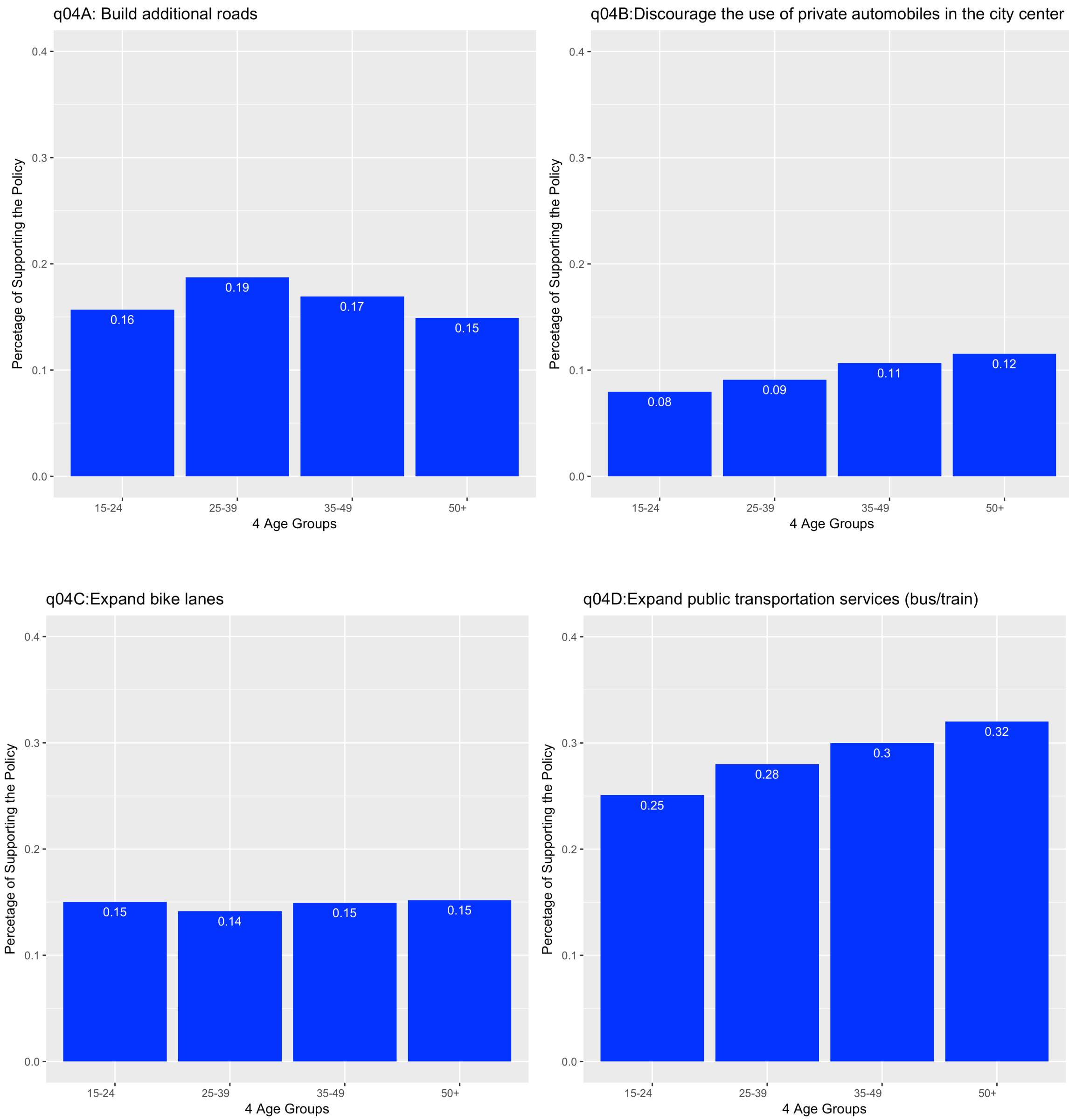
4.2.1 Individual Socio-demographics

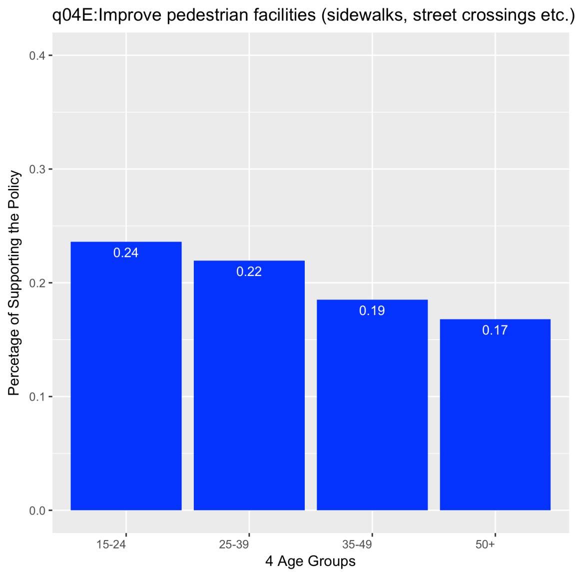
First, the study on age is meaningful. According to the World Bank, by 2030, 16.5 percent of world's population will be aged 60 or older. This demographic trend will therefore call for new solutions that are age-appropriate and elder-friendly (the World Bank, 2017).

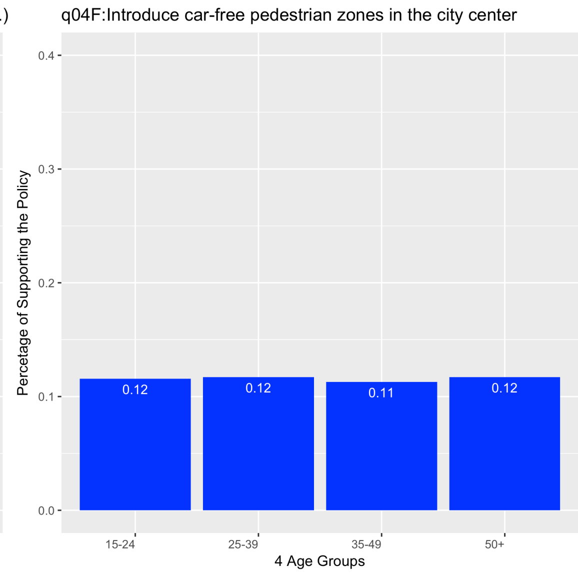
Previous work on age segmentation done by AARP Public Policy Institute (2002), has report on age and mobility policies in particular. The institute argues that the overarching goal for transportation policy is to keep people mobile and thereby able to access the goods, services, work, and social opportunities of their communities. The institute has published a 2002 report on transportation for senior population (50+). This report provides information about how older persons get around, personal characteristics of the older population, and the problems that these individuals perceive with their transportation options. Similarly, the method of age segmentation can be applied here to analyze how different age population respond to 11 policies. This information can help policy makers tailor policy to improve mobility of older/younger individuals, or any target age groups.

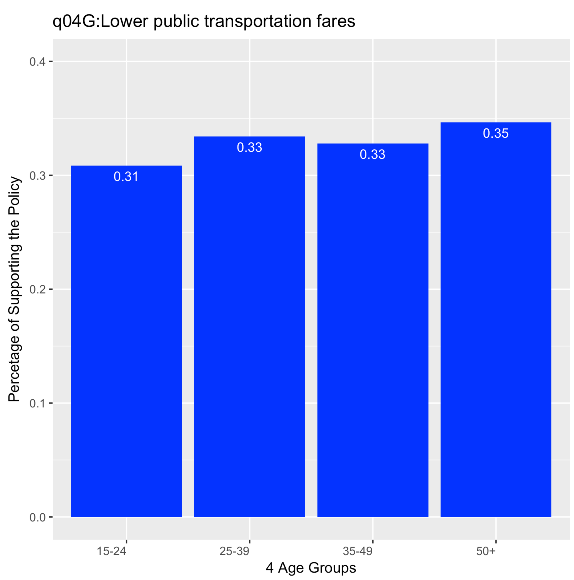
In the model results, the elderly tends to support expanding transit, lowering transit fare (2 public transit related polices), discouraging car and setting car free zones in center city and finally subsidizing energy vehicles. This indicates that older people have the tendency of seeking alternatives other than cars. One reason is that probably they are no longer able to drive. The model has controlled for the fixed effect of car access/car ownership and primary commuting mode, but that is not the whole picture in terms of travel behaviors.

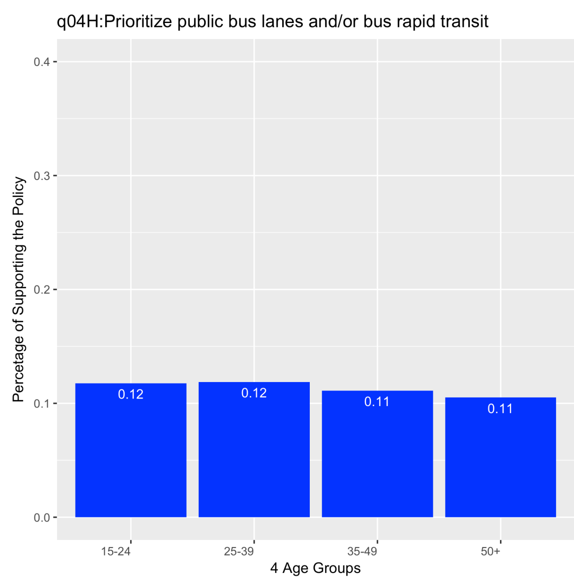
Figure 4.1 Percentages of support of 11 policies with respect to 4 age groups.

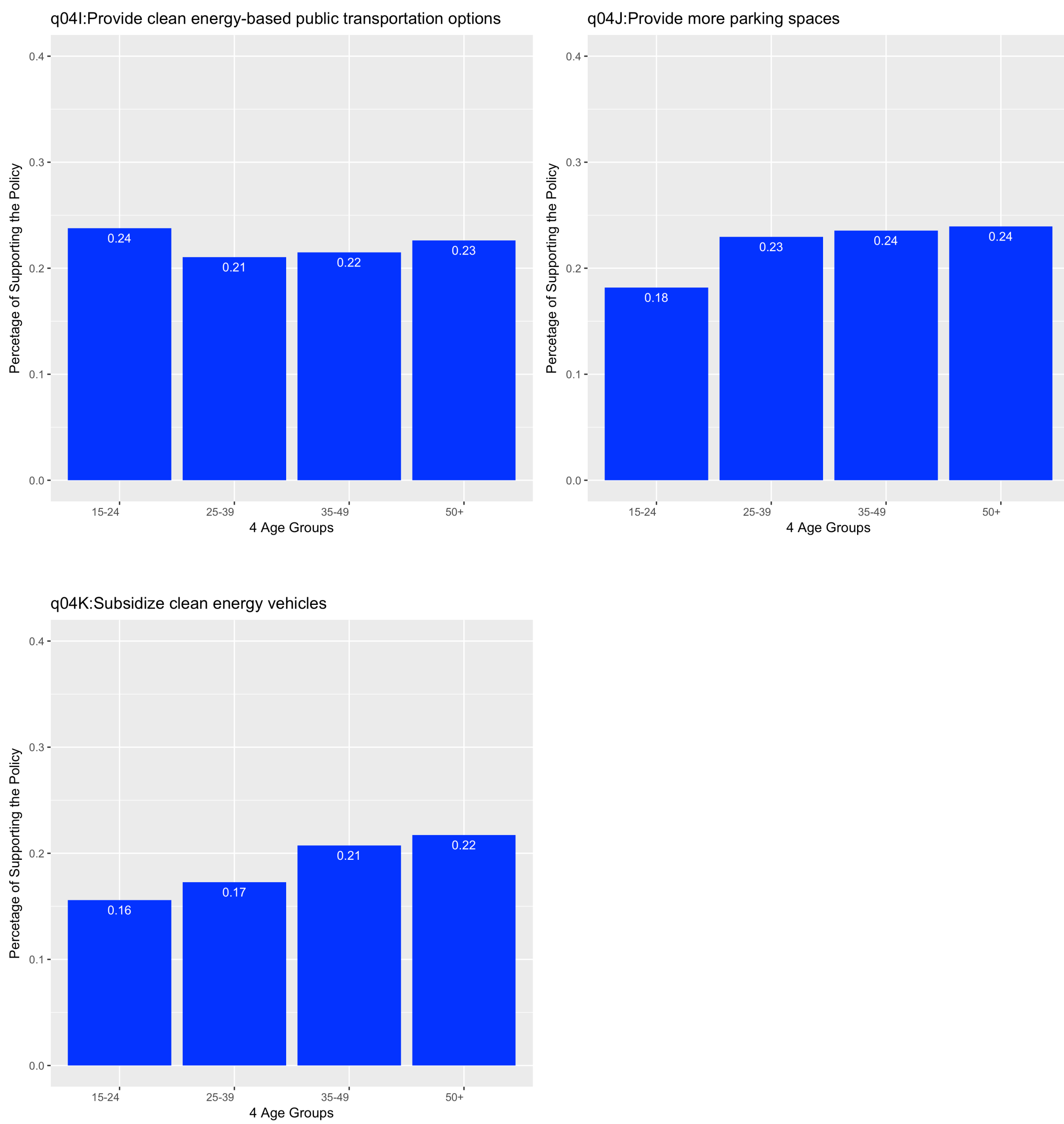



q04E:Improve pedestrian facilities (sidewalks, street crossings etc.)
Percetage of Supporting the Policy
0.0
0.1
0.2
0.3
0.4
0.24
0.22
0.19
0.17
15-24
25-39
35-49
50+
4 Age Groups


q04F:Introduce car-free pedestrian zones in the city center
Percetage of Supporting the Policy
0.0
0.1
0.2
0.3
0.4
0.12
0.12
0.11
0.12
15-24
25-39
35-49
50+
4 Age Groups


q04G:Lower public transportation fares
Percetage of Supporting the Policy
0.0
0.1
0.2
0.3
0.4
0.31
0.33
0.33
0.35
15-24
25-39
35-49
50+
4 Age Groups


q04H:Prioritize public bus lanes and/or bus rapid transit
Percetage of Supporting the Policy
0.0
0.1
0.2
0.3
0.4
0.12
0.12
0.11
0.11
15-24
25-39
35-49
50+
4 Age Groups



We could look closely in Figure 4.1 age brackets based on what we found earlier in the model results. The percentage is defined by number of votes on each policy over the number of individuals falling into the corresponding age brackets. Road does not have a continuously decreasing or increasing order of support with respect to age brackets. Rather, we could tell that age 25-39 has the higher percentage of support of the policy “building additional roads”. For policies including “discouraging the use of private automobiles in the city center”, “expanding public transportation services (bus/train)”, “providing more parking spaces” and “subsidizing clean energy vehicles”, we see an increasing trend of support from elder population groups. This could possibly mean that if government aims to provide services for population groups currently over 50 years old, policies regarding discouraging the use of private automobiles in the city center, expanding public transportation services, more parking and subsidizing clean energy vehicles may be the ones gaining more public support.

On the other hand, we also see policies receiving prioritization/support of a decreasing order from elder population groups. For example, one policy “improving pedestrian facilities” has the highest support rate from population group under age 25: 24% (almost a quarter) of youngest individuals would prioritize the policy of improving pedestrian facilities. 22% of individuals of age 25-39 would support improving pedestrian facilities, 19% of age 35-49 respondents would support it and 17% of people over age 50 would support it. This information suggests that younger generation prefer pedestrian facilities. Therefore, the policy makers may find it helpful to think about pedestrian facilities and supplementary services to improve pedestrian experience if some developments mainly target young consumers. This age effect could represent generational differences in priorities, but it may also be confounded by the fact that younger individuals, in general, have fewer physical impediments to walking than older individuals. Therefore, we do not know if this support of pedestrian facilities will continue as this younger generation ages—due to the lack of longitudinal data, we can only make conclusion about age effects at current stage.

Other policies, such as prioritizing bus lane and BRT, do not exhibit a clear pattern with respect to ages, from the age segmentation method. The implication is that age does not distinguish the support of these policies much.

Next, a lens through gender, aims at the equity pursuit of transport service in a way that “transport will be most effective for development if significant gender differences in demand and impact are properly identified and if transport policies and programs can reflect the full range of transport needs” (The World Bank, 2008-2012). The World Bank has referred the third Millennium Development Goal (MDG 3): promote gender equity and empower women as an objective to study women’s preferences to enhance inclusive transport.

Therefore, understanding the gender disparity in policy preferences and support would inform organizations like the World Bank who can then lead the next move in designing programs with members at local practices.

From the model result table, we can tell that women prefer expanding transit, lowering transit fares, improving pedestrian facilities, more parking and providing clean energy-based public transportation options. Clearly, building road is a preference by male, probably also reflect that male has more inclination with driving. I think it is important to note for programs that focus on gender equality, that women prioritize policies on expansive transit network with lower fare prices. It would be helpful as well to include female-friendly transit or pedestrian facilities to enhance women's experience on those mobility choices.

The study of policy support from low-income and low-education groups can be reflected with welfare reform practices. For example, in the U.S., the Department of Transportation has encouraged community initiatives to develop new process to improve urban transportation system, including focusing on the role of transit in accessing jobs for low-income inner-city resident. Moreover, through the Federal Transportation Act grants early in 1997, five state and local agencies received pilot planning grants from the Federal Transit Administration to "identify job access problems and develop strategies to solve those problems" (U.S. DOT, 1997). The need of identifying low-income and low-education groups' preferences aligns with the pursuit of federal program to promote easy job-accessing transport: if desired services are provided then low-income and education groups are more likely to obtain higher mobility.

Among the 11 policies, we can tell that low-education groups do not support transit-related policies, subsidizing clean energy transit and vehicles, and discouraging car uses in the center city. But here the tension is that low-income users may rely on public transit even if they do not support those policies. The pattern again in high-income group is obvious—high-income group tends to support public transit, bike lane, car free zone in city center, new energy vehicles, etc. Higher income follows a similar pattern with high-education groups in general. We may reasonably suspect that income is correlated with education, so the two give similar results. But that being said, a city or an agency may face general resistances from low-education group on policies like transit expansion or subsidizing clean energy vehicles. There are also necessary communication tasks to educate those people about the outcomes of some policies, and design targeting programs to encourage them using transit, for example, if they do not already feel ready to take on and as those people tend to have negative attitudes on many of the policies.

4.2.2 Location Characteristics

According to the World Bank, in 2014, 54 percent of the world's population lived in urban areas; the share is expected to grow to 60% by 2030 and 66% by 2050 (2017). It is therefore useful to understand how people in large cities view and support transportation policies.

Looking at the variables related to city size, we find that larger cities tend to witness higher support on parking, transit prioritization, lower transit fares, discouraging private car use in city center, expanding bike lanes and providing clean energy-based public transportation options. The findings imply that cities with different population sizes prioritize transportation policies differently. Larger cities tend to have higher parking pressure and high demand on public transit. Policy makers and officials may find it useful to consult these findings and according to their own jurisdictions' condition, understand the possible demand and project the next phase's goals given surveyed public views.

4.2.3 Commuting Mode

One possible audience who cares about travel modes, is the Federal Highway administrative, as it constantly conducted research on travel behavior trends. Findings of the models show that drivers and passengers (who take a ride rather than drive by themselves) of cars, prioritize road and parking policies. Such support reflect that more roads and parking would benefit driving and car-riding utilities. Drivers and passengers would also support policies on subsidizing clean energy vehicles significantly, affirming that policies on clean energy vehicles are attractive to people use car regularly.

Drivers tend to be indifferent or unfavored by policies regarding other modes, except expanding transit services. Both drivers and passengers prioritize transit expansion, but not prioritizing public bus lanes and/or BRT, possibly because they see dedicated bus lanes compete with driving. Drivers do not prioritize policies on lowering transit fare, discouraging car use in center city and expanding bike lanes. But passengers would take a neutral stand on these policies and also support improving pedestrian facilities, introducing car-free pedestrian zones in the city center, and providing clean energy-based public transportation options. Thus, we could tell that passengers, compared to driver, look for alternatives more intensely and have less hostile attitudes toward other modes.

It is clear that people support policies in general that are in their self-interest, but there are also some surprising results, for example, the tension between bike and public transit.

All the modes share somewhat favorable attitude toward public transportation, except bike. Bikers have significantly negative support on roads, parking, transit expansion and lowering transit fares. But bikers support expanding bike lanes, discouraging car use in center city, and introducing car-free pedestrian zones in the city center. It seems that bikers have strong competing nature with cars and transit in this sense.

Similarly, transit riders tend not to prioritize road related policies or bike lane expansion policy. Meanwhile, transit riders would support all public transportation-related policies, including expanding public transportation services, prioritizing bus lane/BRT, lowering transit fares and providing clean energy-based public transportation options. It is interestingly useful to notice the tension and competition of resources among three modes; agencies may anticipate the support and opposition coming from different commuting groups if certain policies targeting on road/transit/bike is going to be announced.

Lastly, walkers/pedestrians tend to be supportive on most of the policies except building additional roads. Pedestrians' supportive attitudes on expanding bike lane and expanding transit service polices imply that walking is complementary to many other modes so that people would not have exclusive preferences over walking against other alternatives.

4.2.4 Car Pride

This is the variable we proposed to include but no prior study has shown its relation to policy support. I hope research institutes that investigated perception of public on infrastructure/goods for sustainable transport, e.g. the World Bank, may find the car pride variable useful.

4.3 Take-away Messages

Using survey data, agencies/institutes/government may be interested in looking at those policies individually and understanding the relative magnitude of support from different groups. Some of the policies regarding bike lane, pedestrian facilities, prioritization of BRT may attract NGOs to design and promote sustainable transportation programs. Local government can also consult those findings to evaluate policies like providing clean energy transit or more parking. It is likely that more parking is always a popular option in many population groups; providing parking may be a safe option for many politicians to gain public support. But since governing entities have different agendas and if other policy items were to implement, different groups can react in many ways and those different attitudes/preferences are worthy of anticipating from a policy-making perspective.

5 Policy Support and Country-level Analysis

This chapter focuses on country level variance in support for transportation policies. The research questions this chapter trying to answer are, if there are country-level variances in policy support and what factors are associated with such variances. To answer this question, we consult the country dummy variables included in the model (see Chapter 3). Each country dummy is coded as 1 if the respondent is in the country, and 0 otherwise. The estimated coefficients for those country dummies represent how and to what extent being in different countries affect individual policy support after controlling for individual characteristics like socio-demographics, travel behaviors, and attitudes like car pride.

The attempts to rank countries and to conduct country index have been adopted for many global issues. For example, The Bertelsmann Stiftung and the Sustainable Development Solutions Network (SDSN) of UN co-produced the 2018 SDG Index and Dashboards report (2018). This report provides overall ranking of countries by the aggregate SDG index of overall performance, to evaluate performance and to project distances from achieving SDGs in 2030. We consulted the ranking concept here also to present countries' transportation policy support and hope to motivate learning and sharing of experience across the border. The ranking of SDG index can also provide insights to the ranking of public policies in this thesis; readers interested in relating the two sets of rankings can check the work of Bertelsmann Stiftung and SDSN.

5.1 Model Results: Country Ranking

Since there are 51 countries/regions in the dataset, the model includes 50 dummy variables that each corresponds to one country with South Africa used as the reference. We use y-standardized coefficients (STDY) from Mplus as recommended when covariates are binary. The STDY coefficient is interpreted as the standard deviation unit change in y when x changes from zero to one (Muthén and Muthén, 1998-2019). Using these standardized coefficients, we can then rank each country by the strength of their support for each policy. The objective of such country level ranking is to see if a person in country X vs. in country Y would have different extent of policy support. Table 5.1 is the full table of the 50 countries' ranking on each of the 11 transportation policies, ordered by the magnitude of support of building additional roads.

A positive coefficient with respect to country X and policy Y means that, being in country X, a person gains "utility" in supporting policy Y and thus we shall observe a higher support from people of residence in country X. For example, if a person is in Russian, Kenya or Bahrain, he/she would support building additional roads to a positively large extent. If the same person (same age, gender, income, etc.) is in Portugal, Spain or Japan, he/she would prioritize the policy support of building additional roads the least. This information is compelling in a way that it aggregates public opinion and makes it comparable across the globe.

Table 5.1 Full table of the 50 countries' ranking on 11 policy support, ordered by the magnitude of support of building additional roads.

Country	More Road	More Parking	More PT	BRT	Lower PT Fares	Car-light CBD	Bike Lanes	Pedestrian Facilities	Car-free Ped CBD	Clean PT	Clean Cars
Russian Federation	0.529	0.668	-0.561	-0.036	0.02	-0.466	-0.137	0.124	0.112	-0.42	-0.281
Kenya	0.486	0.083	0.094	-0.087	0.051	0.205	-0.268	0.14	0.099	-0.18	-0.165
Bahrain	0.379	0.495	-0.421	-0.21	-0.478	0.071	-0.315	-0.075	0.136	-0.566	-0.055
Morocco	0.356	0.091	-0.148	-0.285	-0.09	0.136	-0.175	-0.028	0.349	-0.05	0.348
Philippines	0.345	0.104	-0.122	-0.272	-0.2	-0.106	0.017	0.336	-0.404	0.131	-0.027
Peru	0.297	-0.016	-0.259	-0.261	-0.252	-0.222	0.287	0.288	0.052	0.109	0.032
Poland	0.279	0.561	-0.361	-0.586	0.002	0.019	0.617	0.038	-0.006	-0.436	-0.095
Venezuela	0.263	-0.173	0.254	-0.238	-0.121	-0.575	-0.168	0.437	0.098	0.116	-0.337
Colombia	0.217	-0.198	-0.233	-0.152	0.051	-0.321	0.374	0.159	0.024	0.174	-0.061
Egypt	0.211	0.263	-0.316	-0.065	-0.209	0.052	-0.158	0.228	0.263	-0.24	0.054
Algeria	0.203	0.161	-0.15	-0.238	-0.139	0.178	-0.472	-0.032	0.16	-0.232	0.236
Viet Nam	0.193	0.364	-0.257	-0.11	-0.52	0.153	-0.22	0.59	0.12	0.11	0.186
Ukraine	0.169	0.184	-0.536	-0.317	-0.094	-0.384	0.255	0.087	-0.115	-0.089	-0.111
Pakistan	0.088	0.207	-0.357	-0.342	-0.195	0.013	-0.303	0.154	0.064	-0.078	-0.123
India	0.016	0.265	-0.076	-0.38	-0.402	0.105	-0.223	0.166	-0.032	0.103	0.09
Indonesia	0.008	-0.258	0.089	0.141	-0.543	0.713	-0.345	0.256	0.038	0.09	-0.293
Israel	-0.02	0.237	-0.067	0.037	-0.299	-0.11	0.113	-0.203	-0.111	-0.275	-0.103
Australia	-0.027	0.324	0.084	-0.203	0.202	-0.088	0.043	-0.062	-0.159	-0.207	-0.141
Ecuador	-0.03	0.067	-0.161	-0.177	-0.319	0.028	0.29	0.267	0.073	0.186	0
Turkey	-0.032	0.207	-0.116	-0.044	-0.113	0.01	0.136	-0.002	0.184	-0.18	0.171
China	-0.034	0.509	-0.336	0.22	-0.418	-0.459	-0.079	0.174	-0.139	-0.211	-0.142
Norway	-0.048	-0.067	0.083	0.095	0.51	0.046	-0.038	-0.087	0.06	-0.465	-0.109
Argentina	-0.063	0.029	-0.032	-0.194	0.24	0.114	0.06	0.125	-0.051	0.016	-0.114
Netherlands	-0.072	0.194	-0.11	-0.307	0.342	-0.016	0.074	-0.321	-0.063	-0.582	-0.033
Saudi Arabia	-0.077	0.118	-0.149	-0.133	-0.157	0.032	-0.225	0.048	0.252	-0.346	-0.26
Hong Kong	-0.089	0.309	-0.34	-0.645	-0.159	0	0.079	-0.267	-0.075	-0.328	0.159
Canada	-0.094	0.126	0.032	-0.109	0.057	-0.267	0.048	0.029	-0.143	-0.319	-0.013
United Arab Emirates	-0.112	0.176	-0.299	-0.191	-0.018	0.172	-0.077	-0.183	0.155	-0.534	-0.021
United States of America	-0.12	0.124	-0.136	-0.354	-0.236	-0.195	0.061	0.066	-0.109	-0.174	-0.114
Chile	-0.151	-0.168	-0.212	-0.267	0.088	-0.043	0.44	0.122	0.056	0.097	0.31
Ireland	-0.186	0.177	-0.027	-0.153	0.114	0.019	0.226	-0.076	0.133	-0.225	-0.055
Sweden	-0.205	0.039	0.138	-0.218	0.347	-0.113	0.079	-0.235	-0.159	-0.542	-0.056
South Korea	-0.207	0.68	0.109	-0.304	0.22	-0.692	0.02	0.034	-0.17	-0.505	-0.221
Singapore	-0.21	0.138	-0.021	-0.131	0.167	-0.246	0.082	0.026	-0.208	-0.219	0.118
United Kingdom	-0.213	0.298	-0.254	-0.201	0.103	-0.209	0.116	-0.026	-0.015	-0.295	-0.112
Switzerland	-0.219	0.322	-0.199	-0.161	0.022	0.113	0.204	-0.284	0.165	-0.286	0.035
Italy	-0.22	0.352	0.071	-0.149	0.084	0.178	0.237	-0.057	-0.04	-0.055	0.304
Mexico	-0.223	-0.347	-0.094	-0.149	0.211	-0.188	0.293	0.367	0.153	0.254	-0.079
Greece	-0.248	0.295	-0.091	-0.261	-0.003	0.13	0.402	0.327	0.395	-0.315	-0.119
Malaysia	-0.27	0.142	0.262	0.105	0.232	0.398	-0.209	-0.138	0.114	-0.268	-0.272
Brazil	-0.272	-0.203	-0.128	0.316	0.088	0.131	0.336	0.277	-0.09	0.067	-0.078
Denmark	-0.293	0.196	-0.06	-0.043	0.46	-0.251	0.042	-0.352	-0.144	-0.329	0.183
Thailand	-0.316	-0.154	0.096	0.032	-0.207	0.741	-0.049	0.211	-0.077	-0.416	-0.244

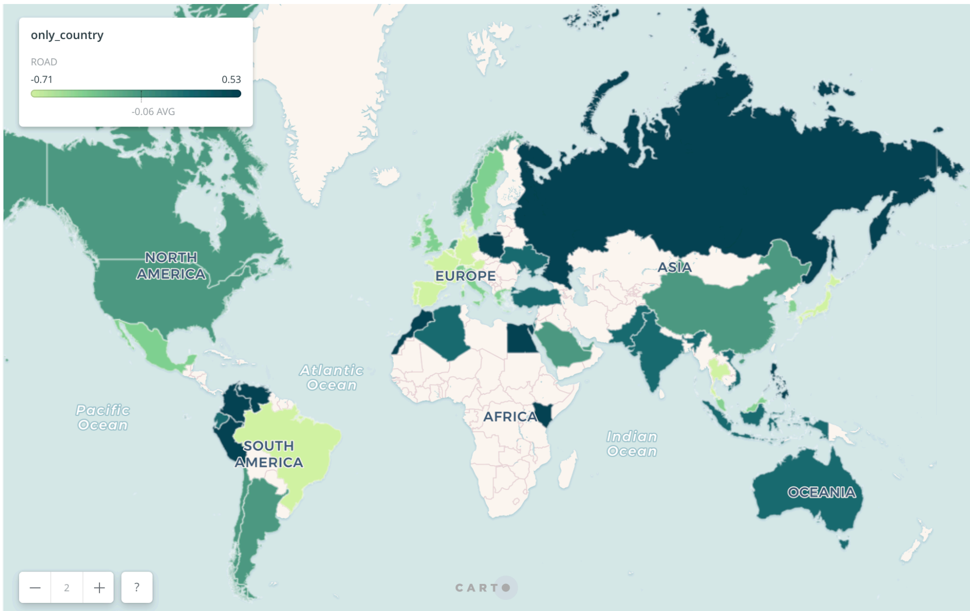
Belgium	-0.343	0.293	-0.088	-0.124	-0.192	0.224	0.281	-0.175	0.062	-0.349	0.114
Germany	-0.347	0.356	0.004	-0.166	0.352	-0.251	0.308	-0.297	-0.07	-0.301	-0.072
France	-0.381	0.352	-0.11	-0.355	0.142	0.217	0.315	-0.131	0.181	-0.014	0.28
Austria	-0.396	0.333	0.146	-0.01	0.255	-0.297	0.201	-0.399	0.029	-0.254	0
Japan	-0.409	0.223	-0.036	-0.432	0.145	-0.22	0.288	0.091	-0.522	-0.448	-0.079
Spain	-0.48	0.288	-0.029	-0.264	0.308	-0.028	0.119	-0.12	0.148	-0.149	0.267
Portugal	-0.715	0.076	0.007	-0.006	0.264	0.276	0.224	0.026	0.039	-0.046	0.19

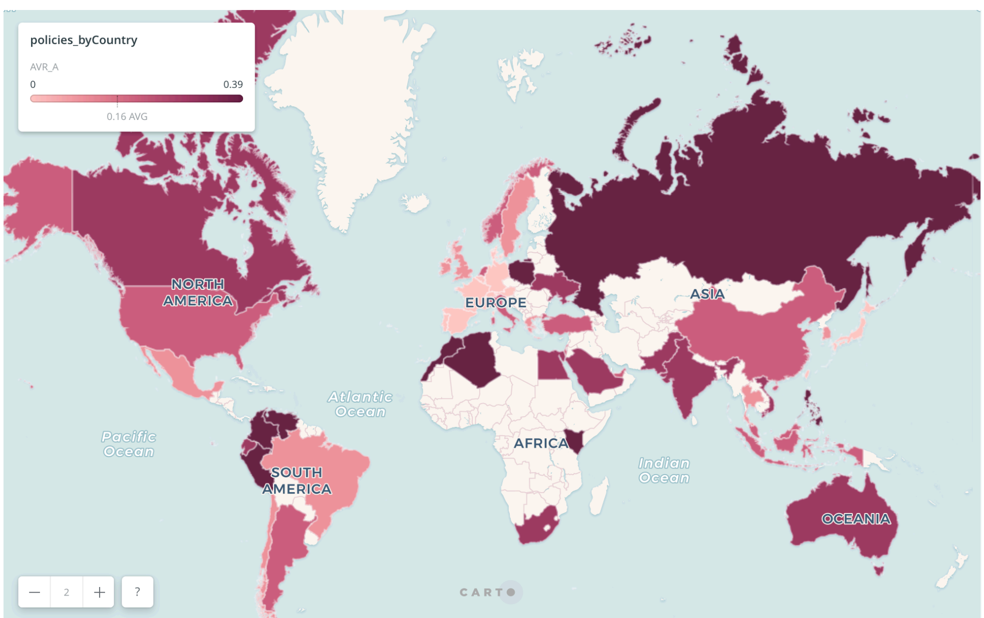
To better visualize the country scores, we can consult the maps in Figure 5.2 (in green). Note that this set of new maps is different from the set of maps (in pink) that were included in Chapter 3. The first set of maps in pink shows the weighted average policy support by countries. The maps in this chapter plot the dummy variable coefficients for the country rankings that have been controlled for possible individual-level effects in the overall support variances.

The contrast between the weighted average support by countries shown on the bottom is not visually outstanding. Actually, the pattern is pretty similar between the two maps. A correlation table between the two set of scores (weighted average support by countries and country ranking scores) is shown in Figure 5.2 where "_avr" in the end indicates the weighted average, explained in Chapter 3. The correlations between country rankings and weighted averages are high.

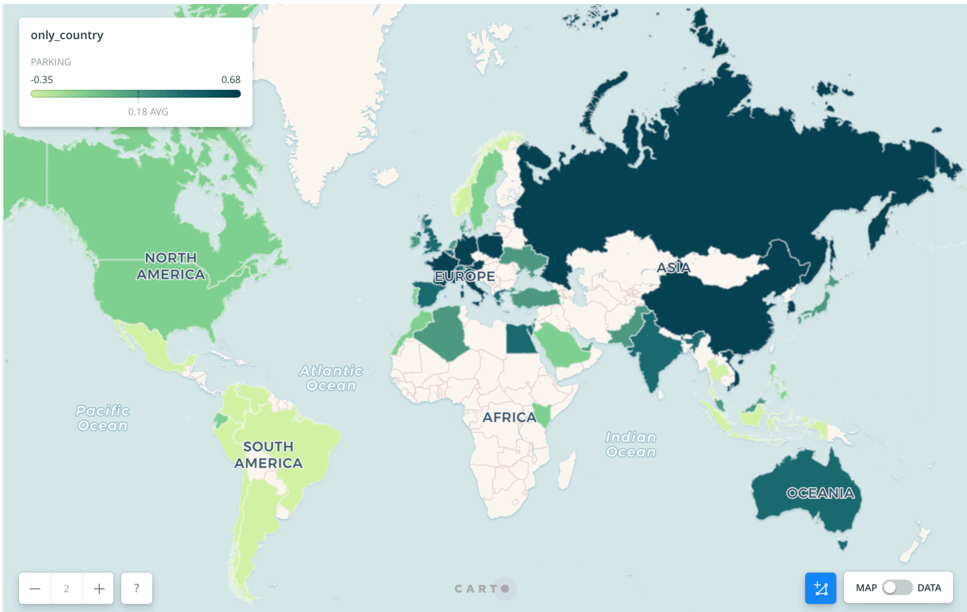
Figure 5.1 i-xi country ranking map (top) shows country variances after taking out all the individual-level effects. Average support by countries is shown on the bottom.

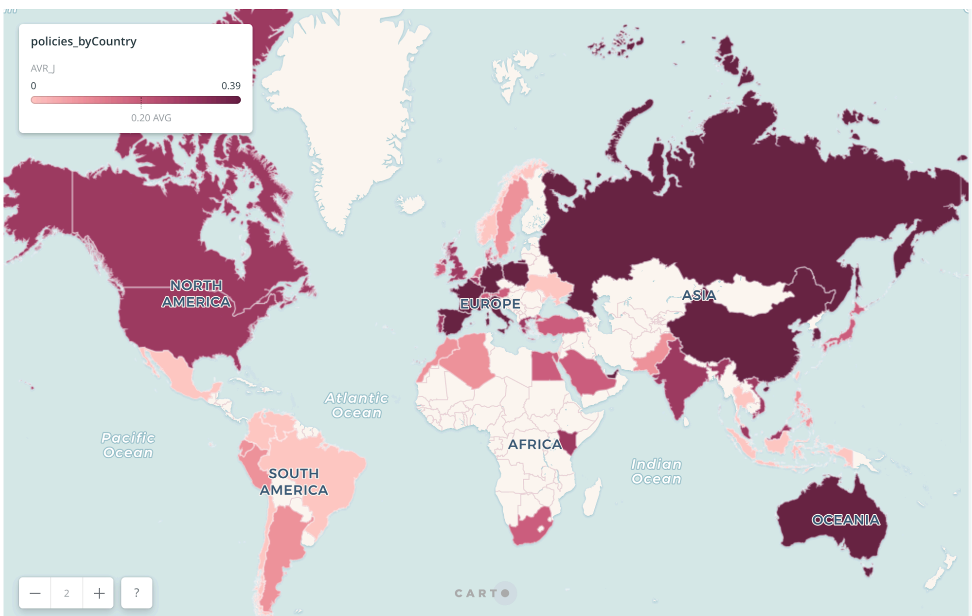
(i) Building Additional Roads.



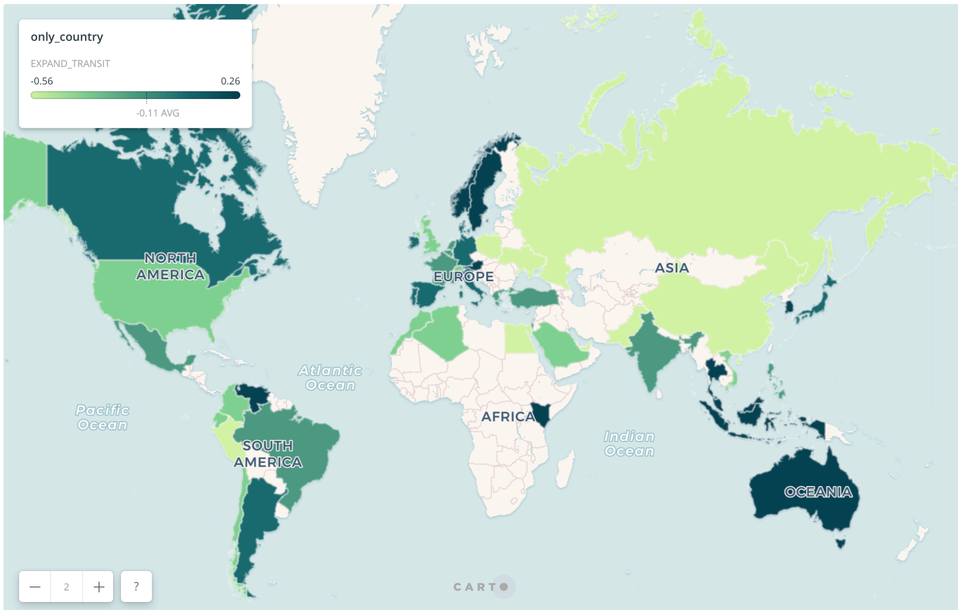


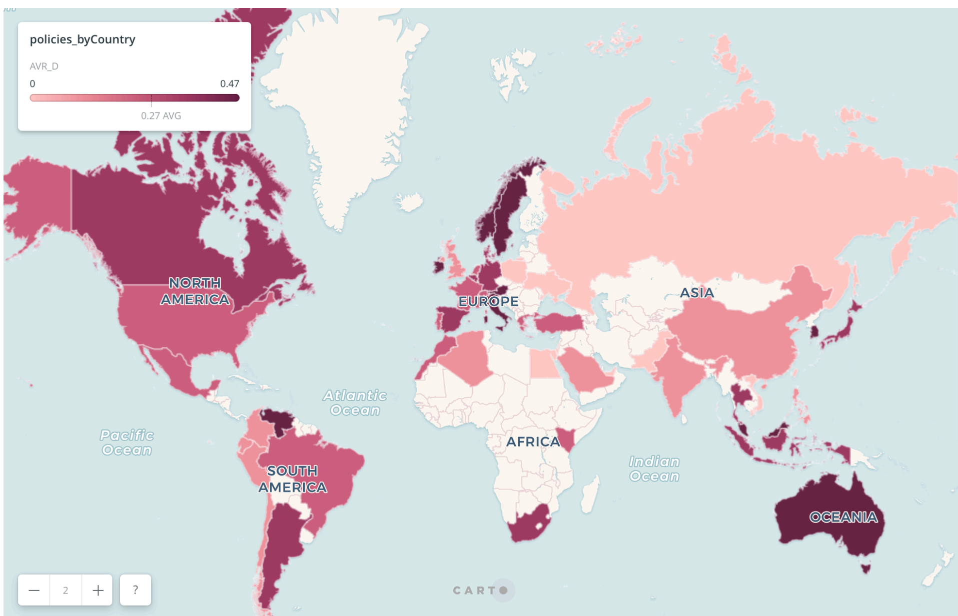
(ii) More parking



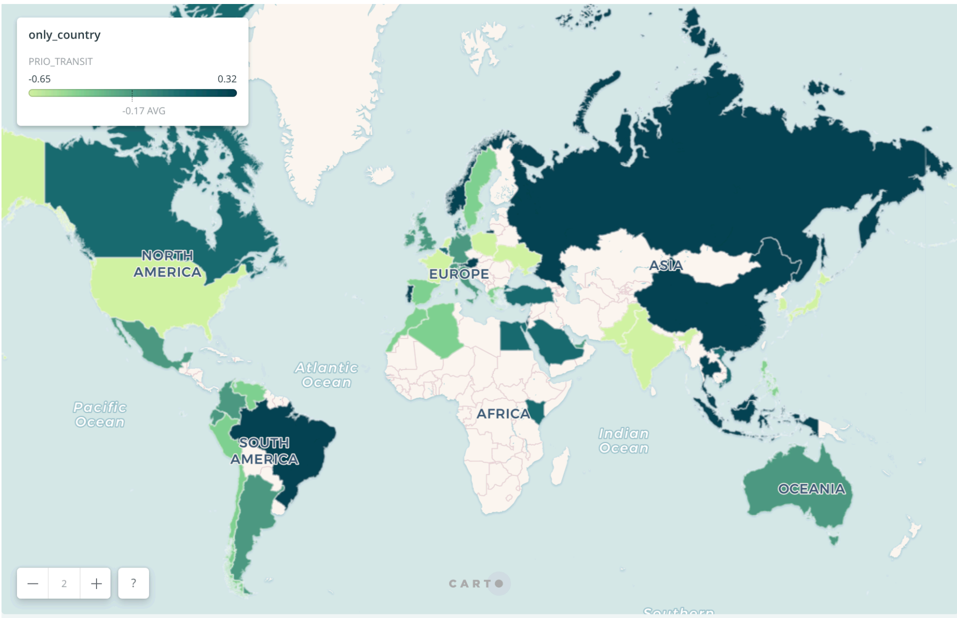


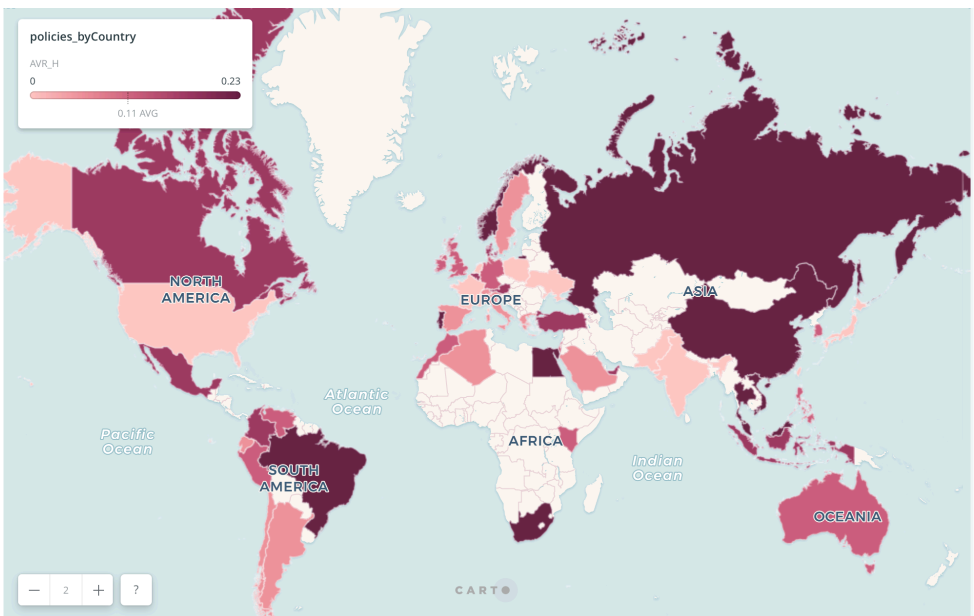
(iii) Expand Transit



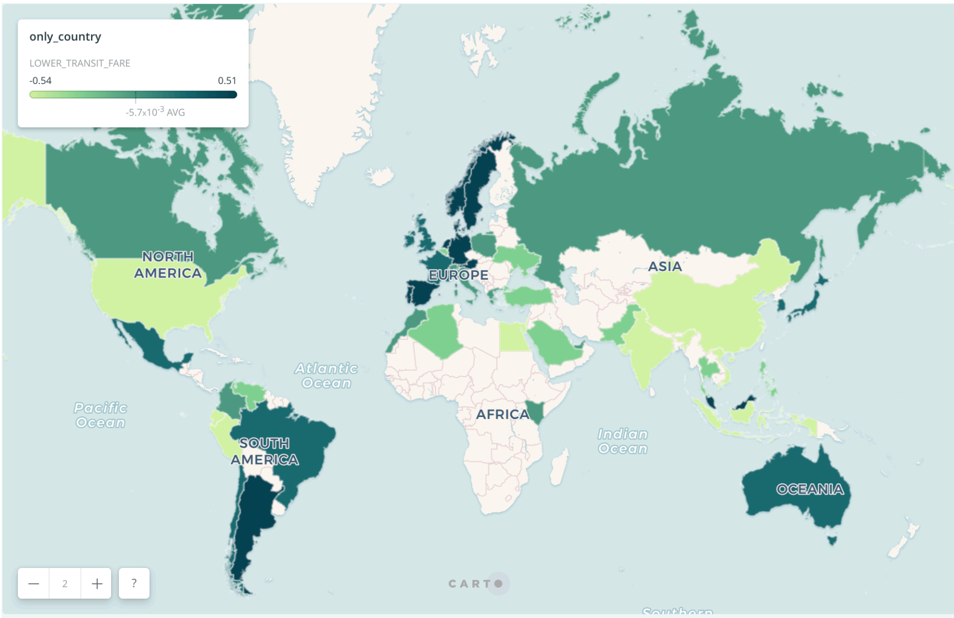


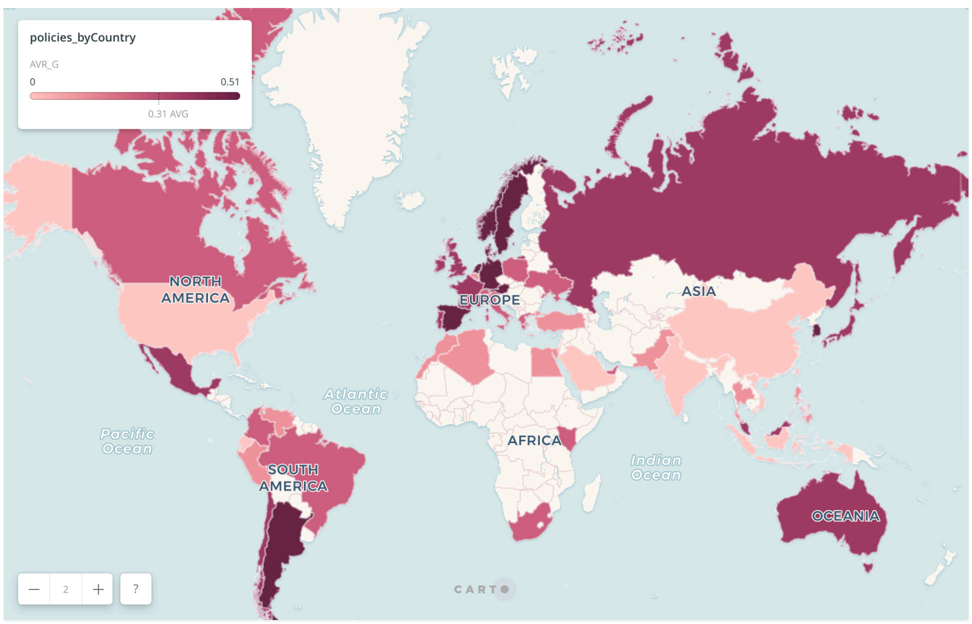
(iv) Prioritizing BRT/bus lane



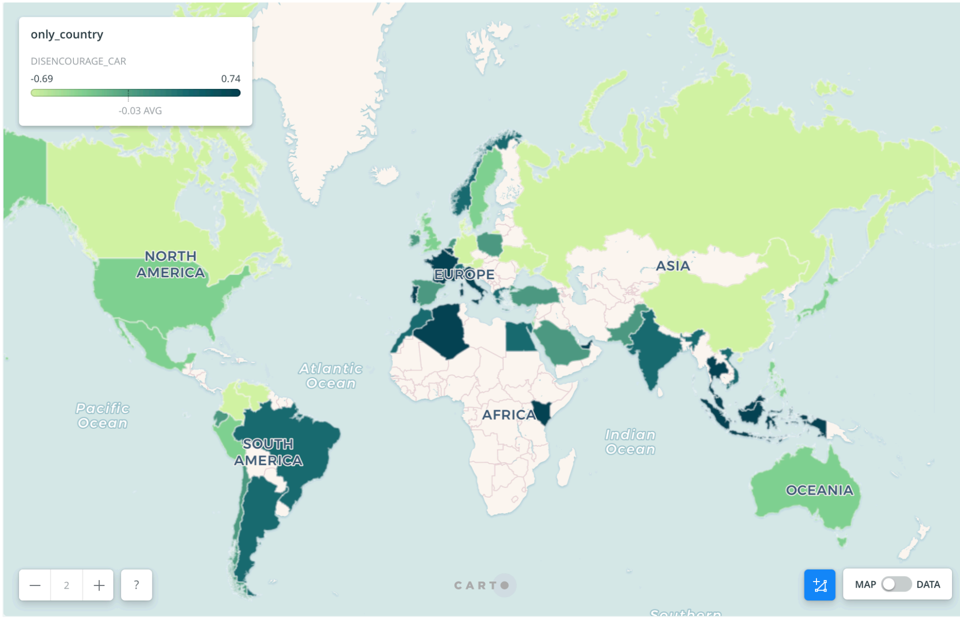


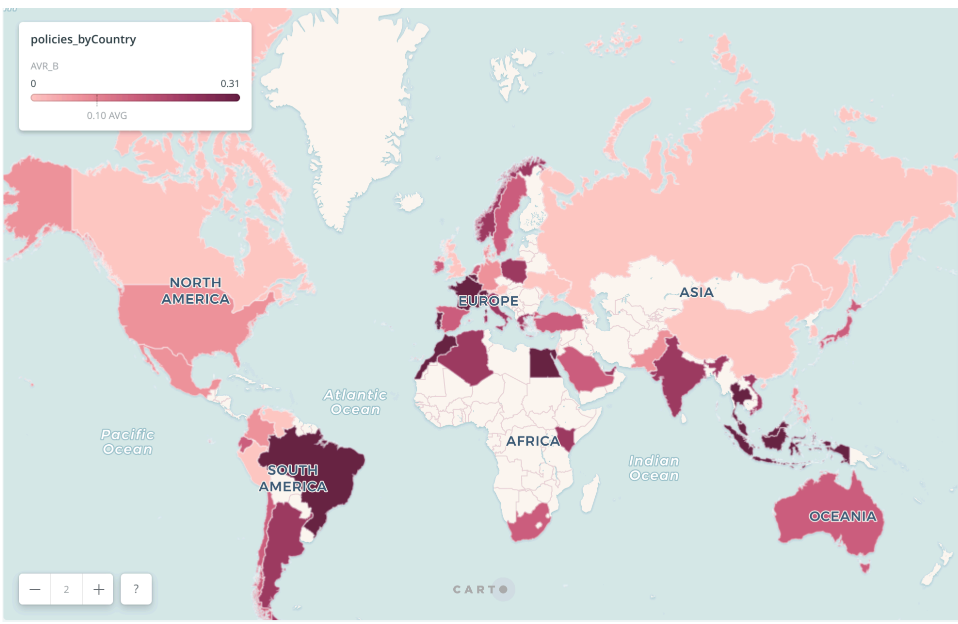
(v) Lower public transportation fares



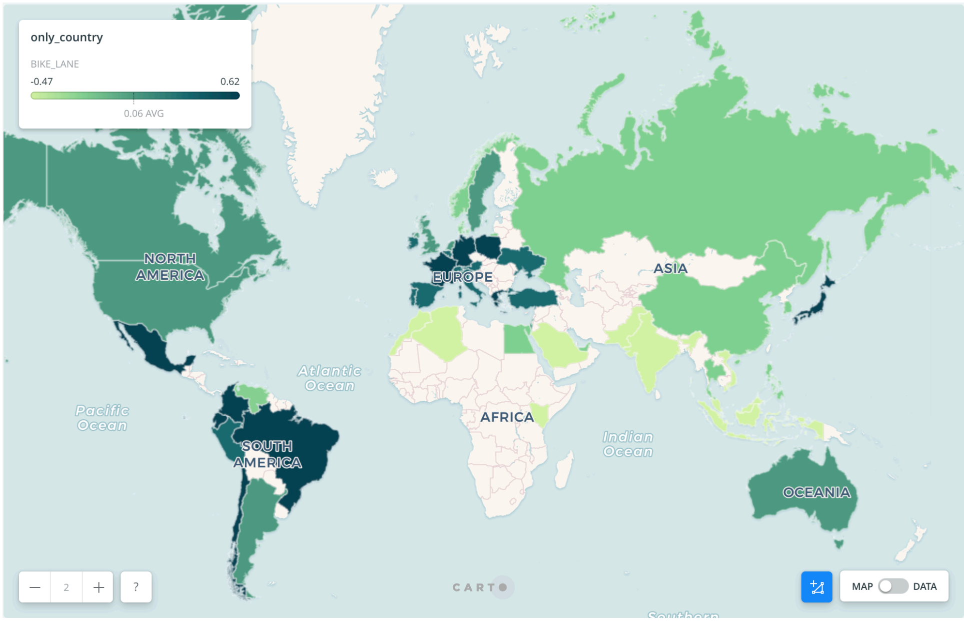


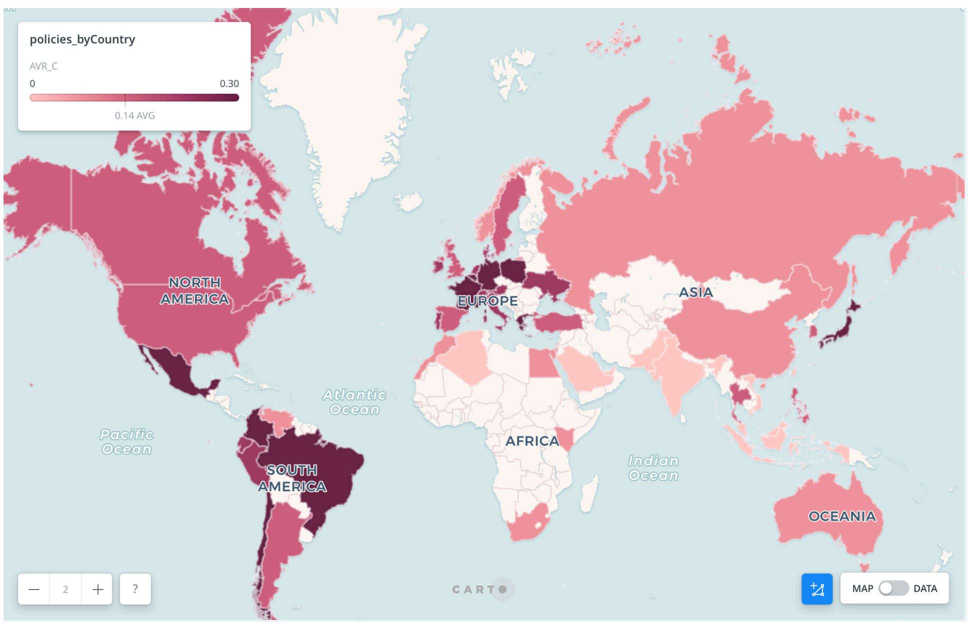
(vi) Discourage the use of private automobiles in the city center



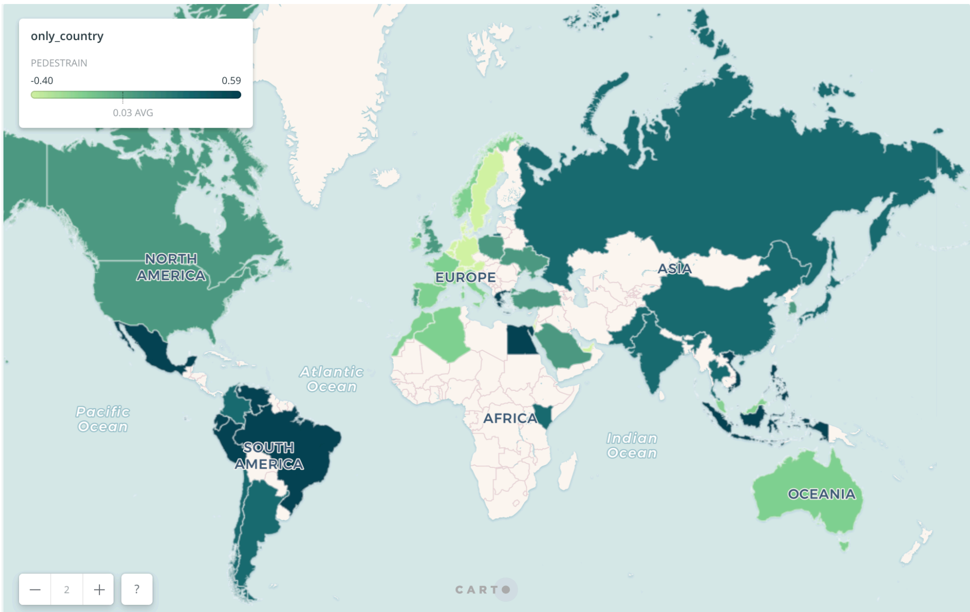


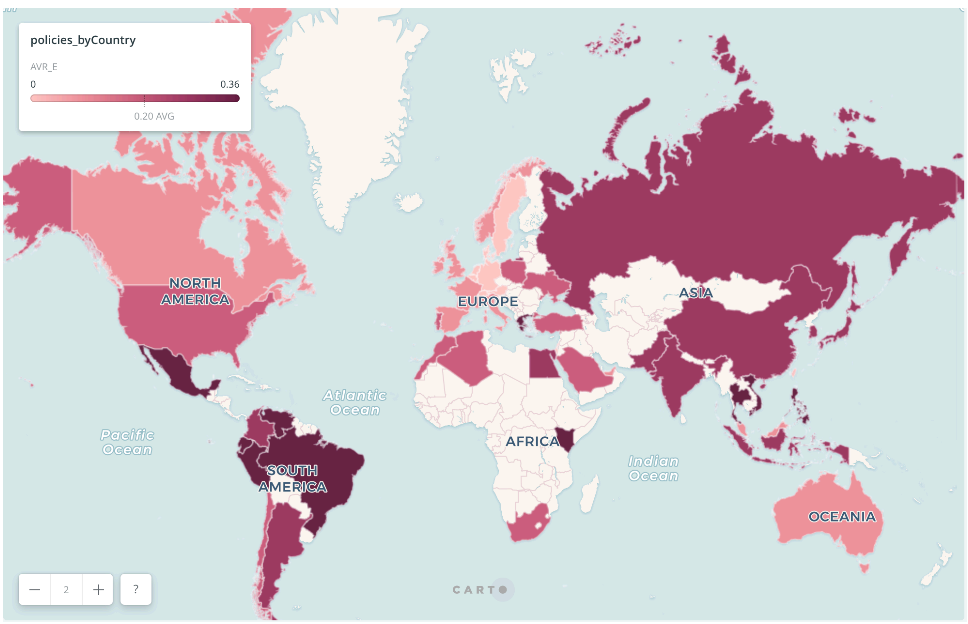
(vii) Expanding Bike Lanes



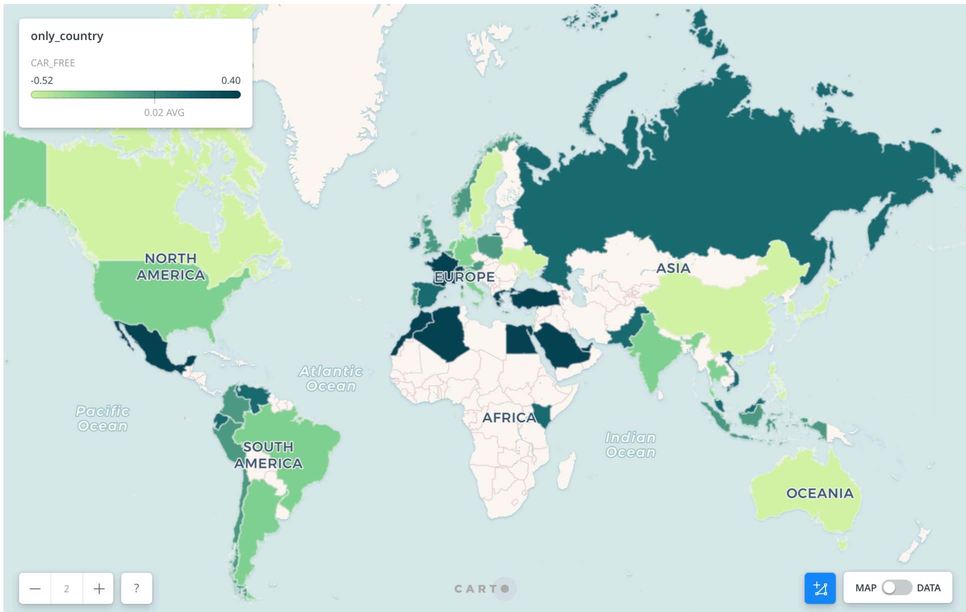


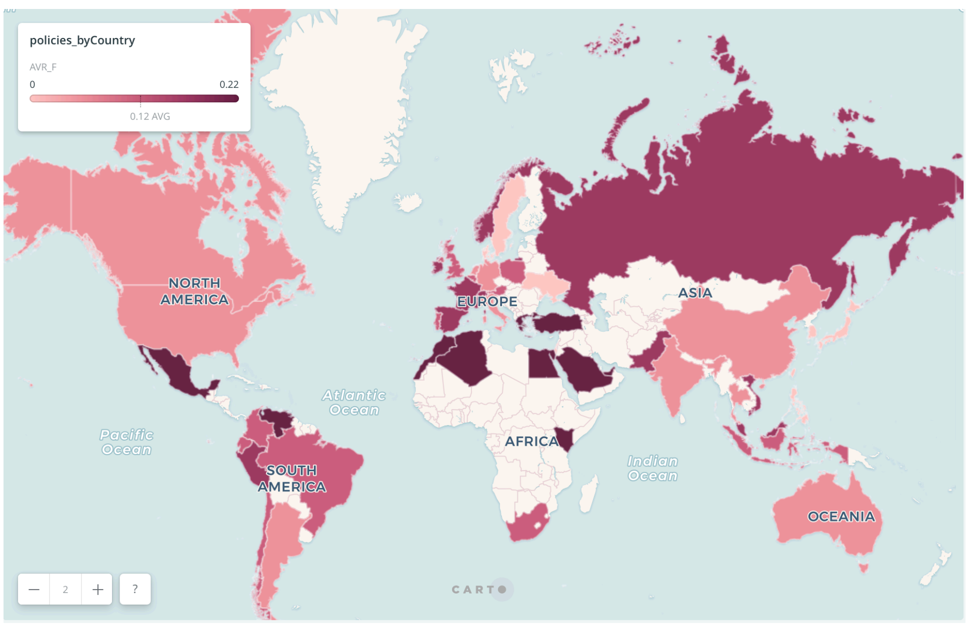
(viii) Improving Pedestrian Facilities



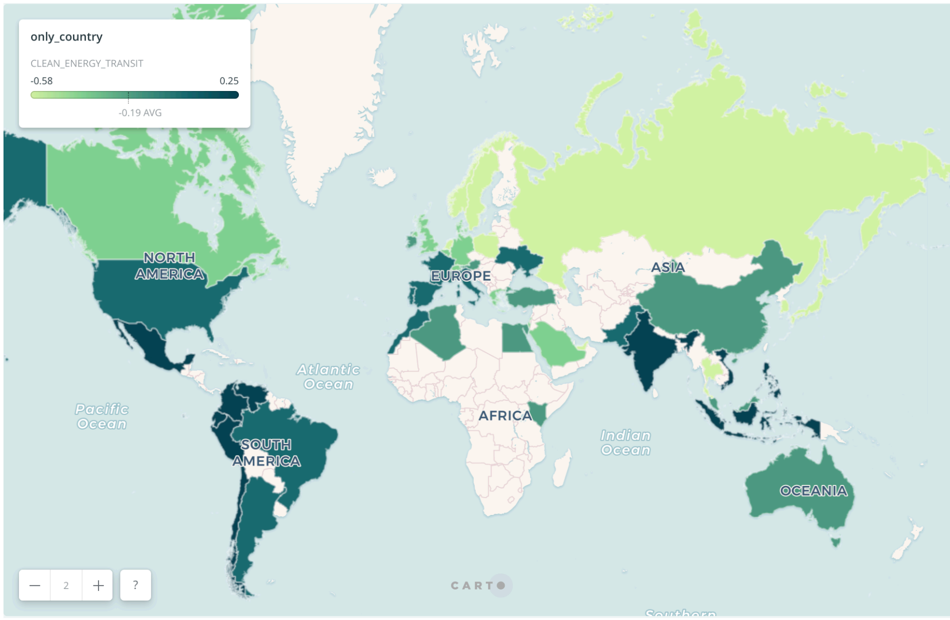


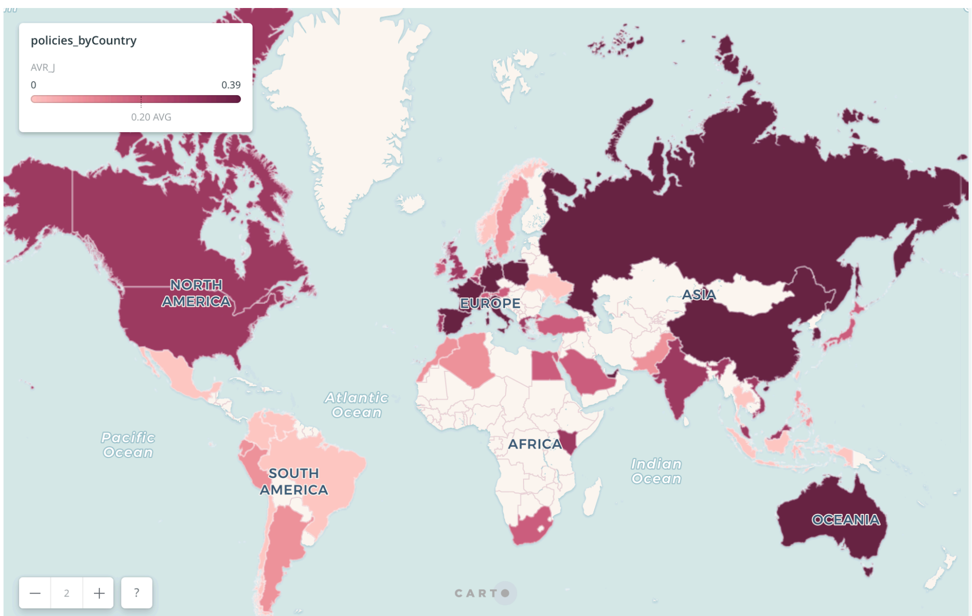
(ix) Introduce car-free pedestrian zones in the city center



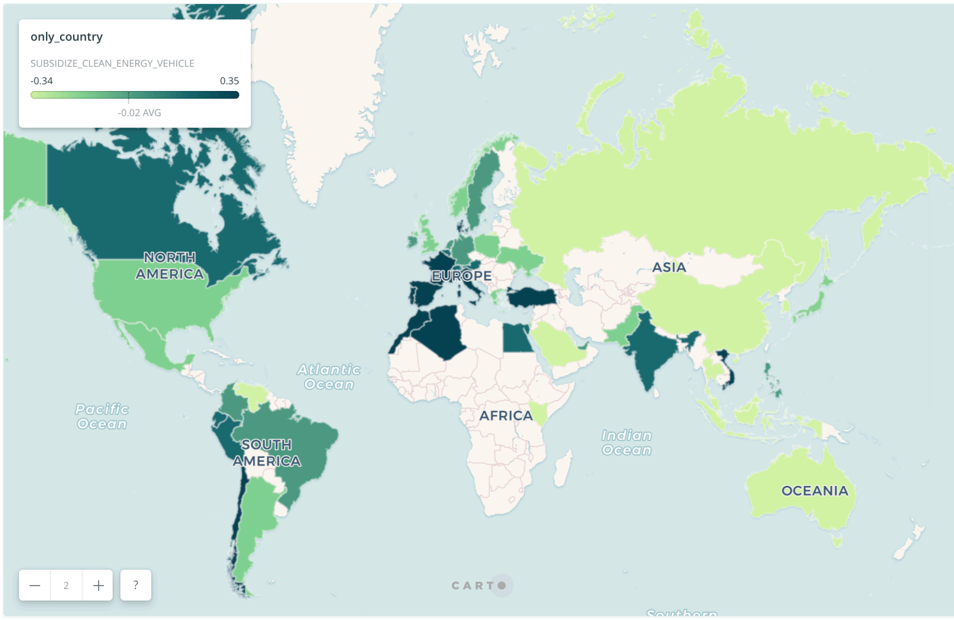


(x) Provide clean energy-based public transportation options





(xi) Subsidize clean energy vehicles



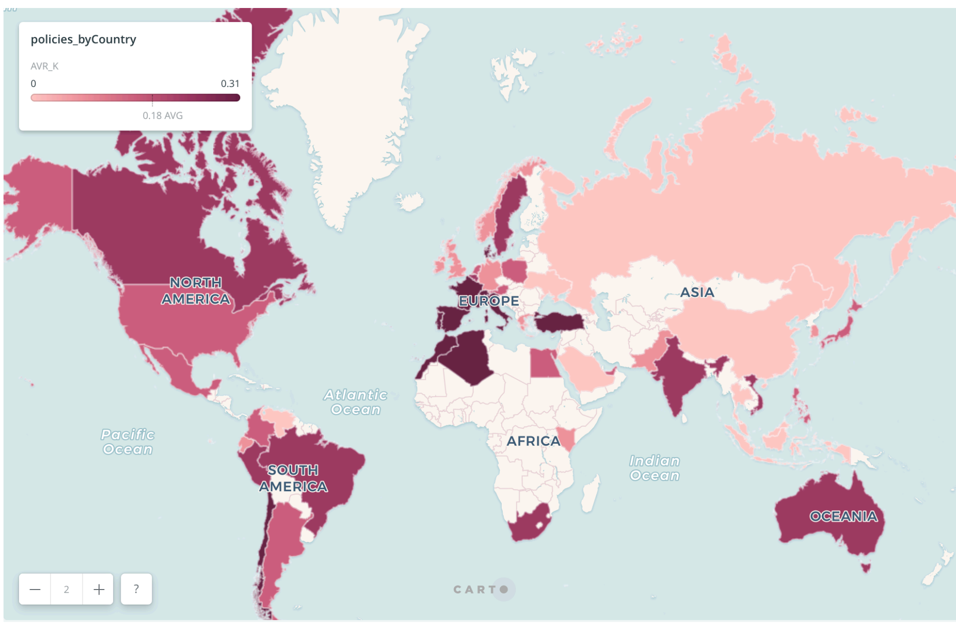
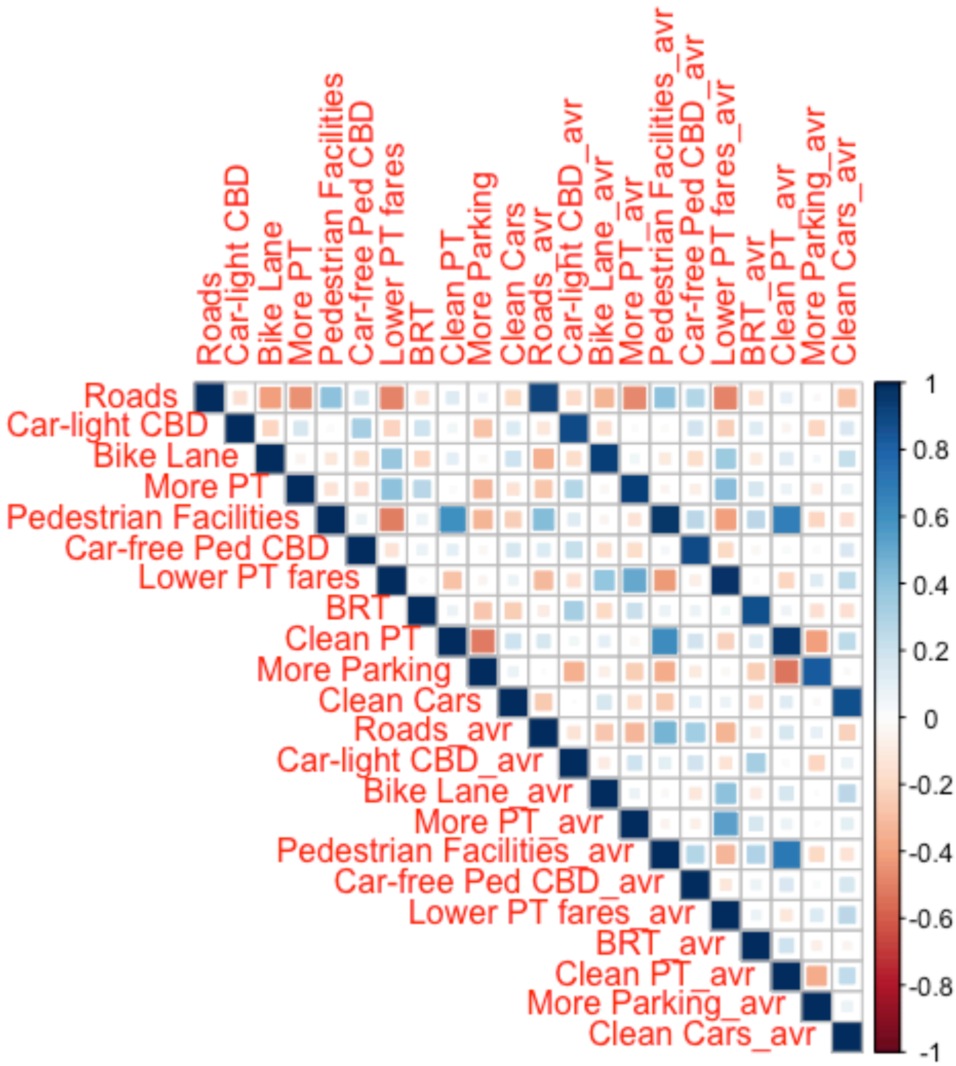


Figure 5.2 Correlation between country ranking scores and weighted average of support by countries.



This country-level comparison informs that that people in different countries desire different services. If NGOs like the World Bank plans to promote active transport programs, the institutes may want to consult the scores of country-level ranking and determine the top countries where the program is likely to be welcomed and bottom countries where the public support is generally weak. For example, for expanding bike lanes, Poland, Chile, Greece, Columbia, Brazil, France, Germany, Mexico, Ecuador and Japan are the top10 countries that prioritize the support most. However, these 10 countries do not exactly align with top ten that use bicycles the most. By the statistics of number of bicycles per capita in year 2011 (TOP10HELL, 2011), the top 10 countries in the world are Netherlands, Denmark, Germany, Sweden, Norway, Finland, Japan, Switzerland, Belgium and China (ordered by ranking). We can tell from the two sets that only Germany and Japan which already rank among the top 10 countries of highest bicycle per capita also rank high in the policy support for expanding bike lane. The number one country in bicycle usage is Netherland where 27% of all trips and 25% of trips to work are made by bikes. To make a comparison, in the USA, only 0.9% of all trips are made by bike. Nevertheless, Netherlands ranks number 26 in 50 countries and the U.S. ranks 27 in terms of the policy support of expanding bike lanes, informed by the country dummy coefficients. That means, given the same socio-demographics and travel behaviors of a person, a Netherlander and an American would not have strong difference in supporting expanding bike lane policy, except that the Netherlander has more probability of using bicycle and he/she is in a more intense culture atmosphere of using and owning bicycles.

Demark and Sweden only rank 31 and 25 in the bike lane expansion policy support, though the numbers of bicycles per capita rank the second and fourth internationally. The intuition is that countries have "best" environment/reputation/culture of biking do not necessarily have the highest support on more of such infrastructure or services. This creates a good opportunity for NGOs to advocate for bike programs in countries/regions that do not have well recognized infrastructure or services, but residents desire such thing. For example, if the World Bank is searching for a pilot site for biking programs, Chile and Columbia would be better that Demark and Netherland, since Chile and Colombia show higher public support on the expanding bike lane policy than Demark and Netherland; also, because Chile and Columbia do not seem to have infrastructure/services as good as Demark and Netherland. Chile and Columbia may be better choices compared to Indonesia and Algeria on the other hand, where the policy support of expanding bike lanes in the latter two countries ranked the lowest. That means, in Indonesia and Algeria prioritize different services, so implementing bike programs there might be less effective and popular.

It is also useful for governments to use the country ranking scores to position themselves. Many countries including China and EU have emphasized on clean energy vehicles. A high desire on the subsidizing clean energy vehicles could be a sign that people in those countries have broad desire of owning clean-energy vehicles; implementing those subsidizing policies would encourage the adoption of clean-energy vehicles (if we are only looking at clean-energy options, ignoring that maybe such policy results in more vehicle ownership). Morocco, Chile, Italy, France and Spain are the top five countries where residents prioritize the clean-energy vehicle subsidies most. The results might alert the officials that the desire of new energy vehicle subsidies exists; whether to subsidize and how much to finance would be the next economic questions for designing the policy metrics.

5.2 Examination of Country-level Factors

One step further is to investigate what might explain these observed variations policy support across countries. By glimpsing the results of supporting building additional roads, I found that developed countries/wealthy countries tend to support less on road policy. To grasp the whole picture of 11 policies, I constructed correlation matrices for 11 policy support items with respect to national level variables, including national GDP adjusted by purchasing power parity, passenger road kilometers per capita, and number of registered vehicles per capita, population density by nation area (population/km^2) and percentage of urban population. These variables suggest economic development level, urbanization rate, car ownership and serve as proxy to national car use. All the aspects can describe an environment one person is situated in, that possibly affect public opinion on what policies to prioritize given the status quo.

GDP per capita and percentage of urban population were obtained from the World Bank website of data of the year 2016. Passenger kilometers by road transport was obtained from the United Nations (UN data, 2015) as a proxy for national car usage. The number of registered vehicles in the country was obtained from the World Health Organization (WHO)'s Road Safety Statistics (WHO, 2013). Both the passenger kilometers by road transport and number of registered vehicles were divided by total population estimates from the World Bank to obtain per capita measures. The two variables are called "PassKm per Cap" and "RegVeh per Cap" in the following writing. "PassKm per Cap" has been log-transformed due to the skew distribution across 51 countries. Gini index could be included, but 10 out of 51 countries are missing this variable; for countries that have Gini indices available, the data come randomly from year 2011 to 2015. Missingness and inconsistence of this variable led us to drop Gini index from the list of country-level variables.

Correlation matrices will show to what extent country-level variables correlate with different national-level policy support. One can think that the number of registered vehicles per capita correlates with the support on road policies but not necessarily with expanding public transportation services, for example. I run the correlation three times: first for all countries, second for developed countries, and third for developing countries, dropping the two countries categorized as "in transition" (Ukraine and Russia). These correlations are visualized in Figure 5.3, Figure 5.4 a, and Figure 5.4 b, respectively. The correlation ranges from -1 to 1 and darker color means stronger correlation. It is likely that the pattern of policy support with respect to national factors follows different paths for developed countries and for developing countries; separating the two types therefore helps inform policy patterns and trends specifically.

Figure 5.3 Correlation table of 11 policy ranking scores and 5 country-level factors, for all 50 countries.

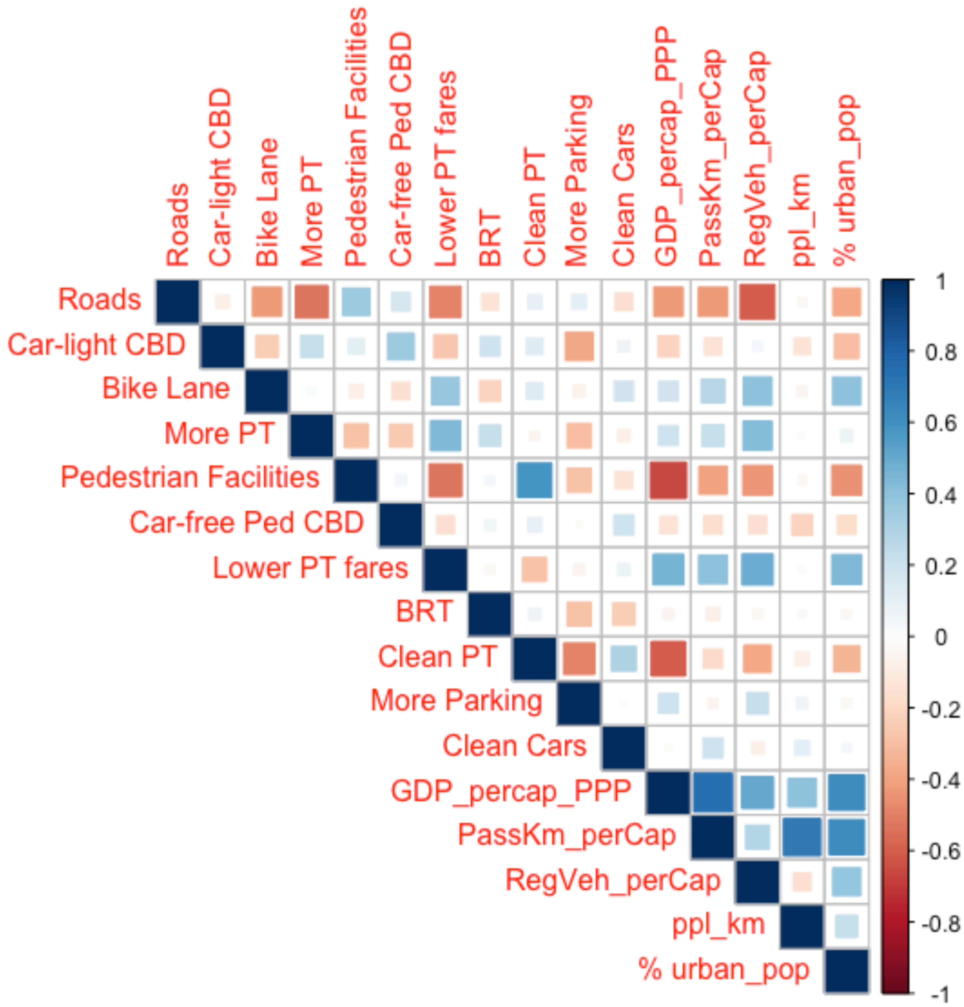
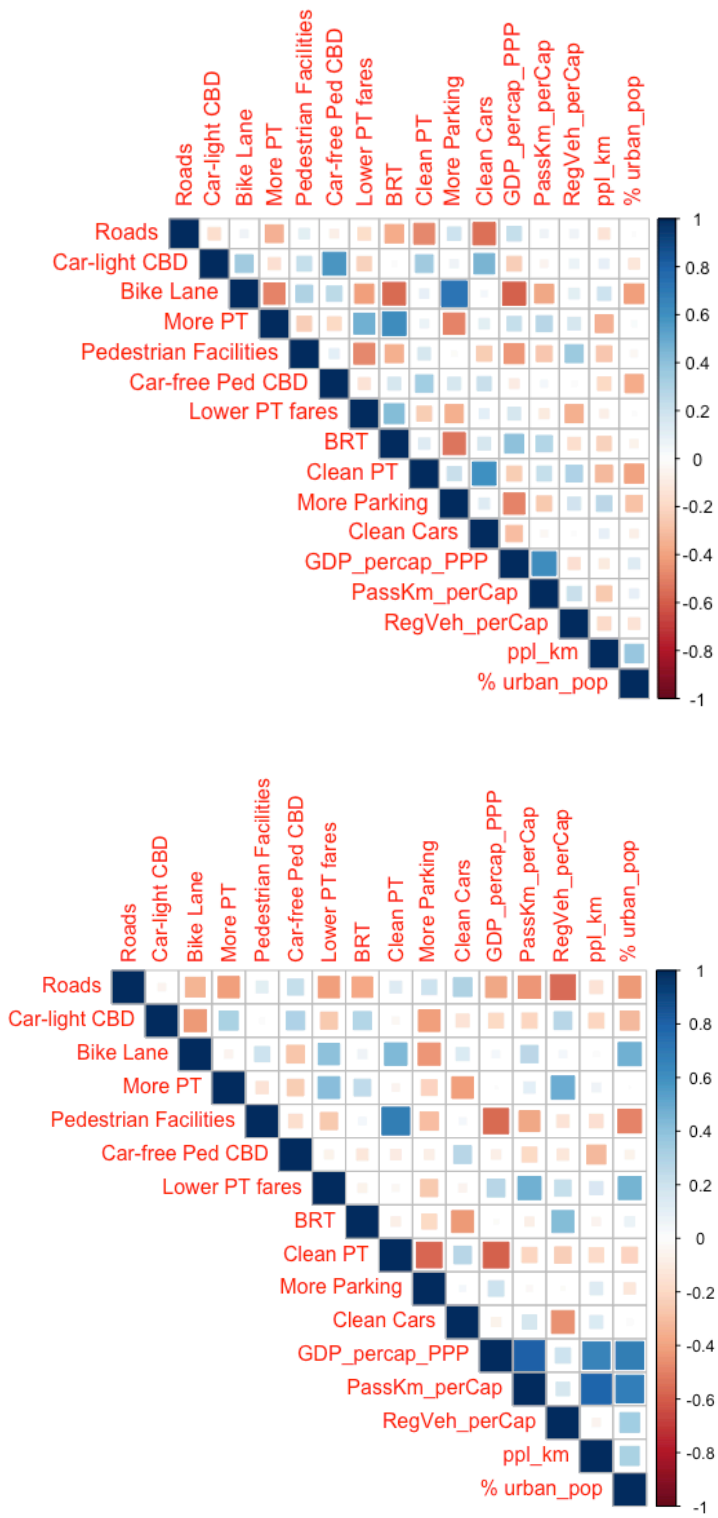


Figure 5.4 Correlation table of 11 policy ranking scores and 5 country-level factors, (a) for 20 developed countries (upper) and (b) for 28 developing countries (lower).



By following the cells on the upper right-hand side of the matrix, we can find correlations between policy support and country-level factors. Darker color indicates stronger correlation, either in blue (positive correlation) or in red (negative correlation). To better compare the three cases, I constructed Table 5.2 in which I only mark the cells with correlations of magnitude 0.35 or greater. Population density (normalizing population by nation area km^2) does not correlate with any policy support items strongly, so it is excluded from Table 5.2.

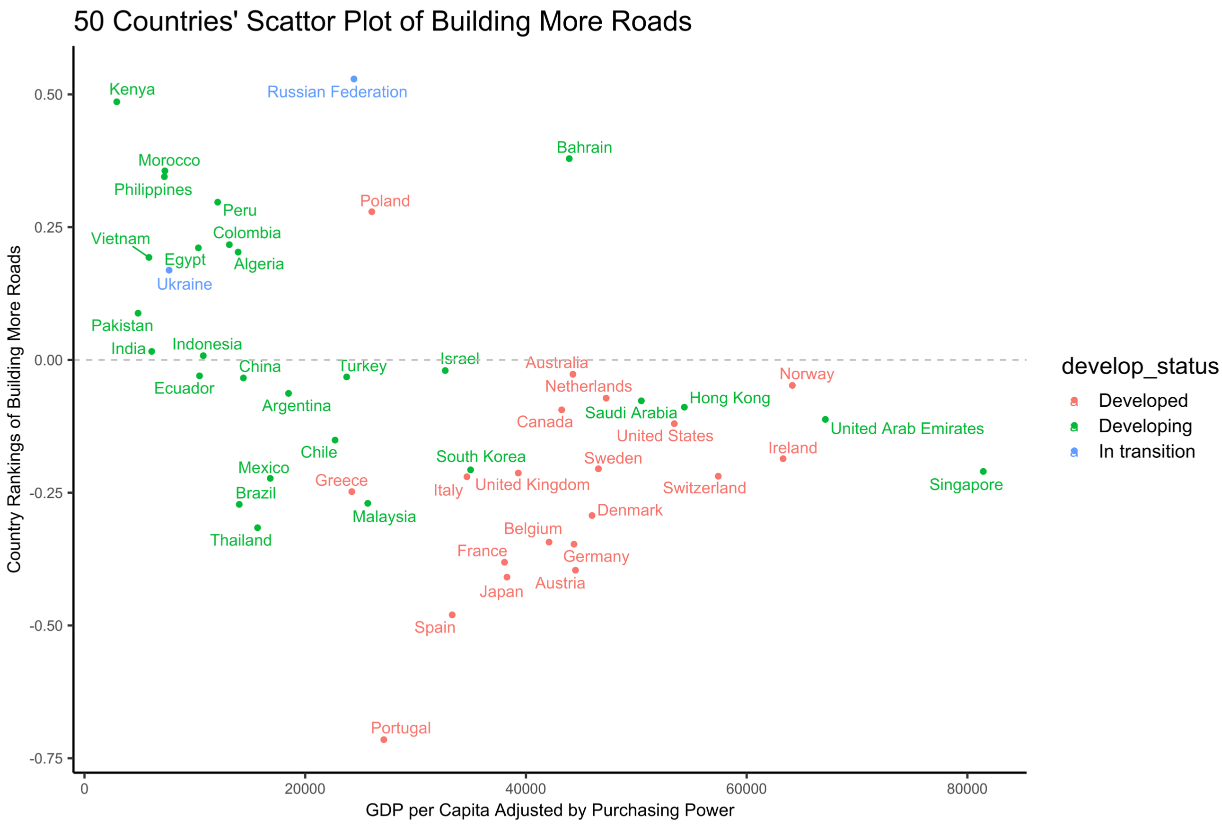
Table 5.2 *Correlations among 11 country-level policy support and country factors for all countries, 20 developed countries and 28 developing countries.*

	GDP per capita			**PassKm per Capita**			**RegVeh perCap**			**% Urban Pop**		
Policy Items	All	Developing	Developed	All	Developing	Developed	All	Developing	Developed	All	Developing	Developed
More roads	-0.43	-0.38		-0.42	-0.44		-0.6	-0.56		-0.38	-0.42	
Car-light CBD												-0.42
Bike lane			-0.59			-0.38	0.40			0.39	0.48	
More PT							0.42	0.48				
Pedestrian facilities	-0.66	-0.56	-0.44	-0.39	-0.38		-0.44		0.35	-0.44	-0.49	
Car-free ped CBD												-0.36
Lower PT fares	0.47			0.41	0.47		0.48		-0.35	0.44	0.47	
BRT			0.39					0.43				
Clean PT	-0.59	-0.59					-0.37					-0.4
More parking			-0.49									
Clean cars								-0.46				

5.2.1 GDP per Capita

From Table 5.2 we can discern that GDP per capita negatively correlates with country-level support on building more roads as well as the construction of additional pedestrian facilities and investments in clean public transportation. Developing countries share similar correlation pattern here, but this is not the case with developed countries. In particular, the correlation of GDP per capita with support of building more roads is much less strong among developed countries compared to developing countries. We may suspect some threshold effect here that once countries enter the phase of developed status, building additional roads is less prioritized as one of the top policy support items. In this case, it may be helpful to visualize the trend by scatter plot. For example, Figure 5.5 shows the scatter plot of the country-level support of building additional roads vs. GDP per capita (adjusted by purchasing power parity).

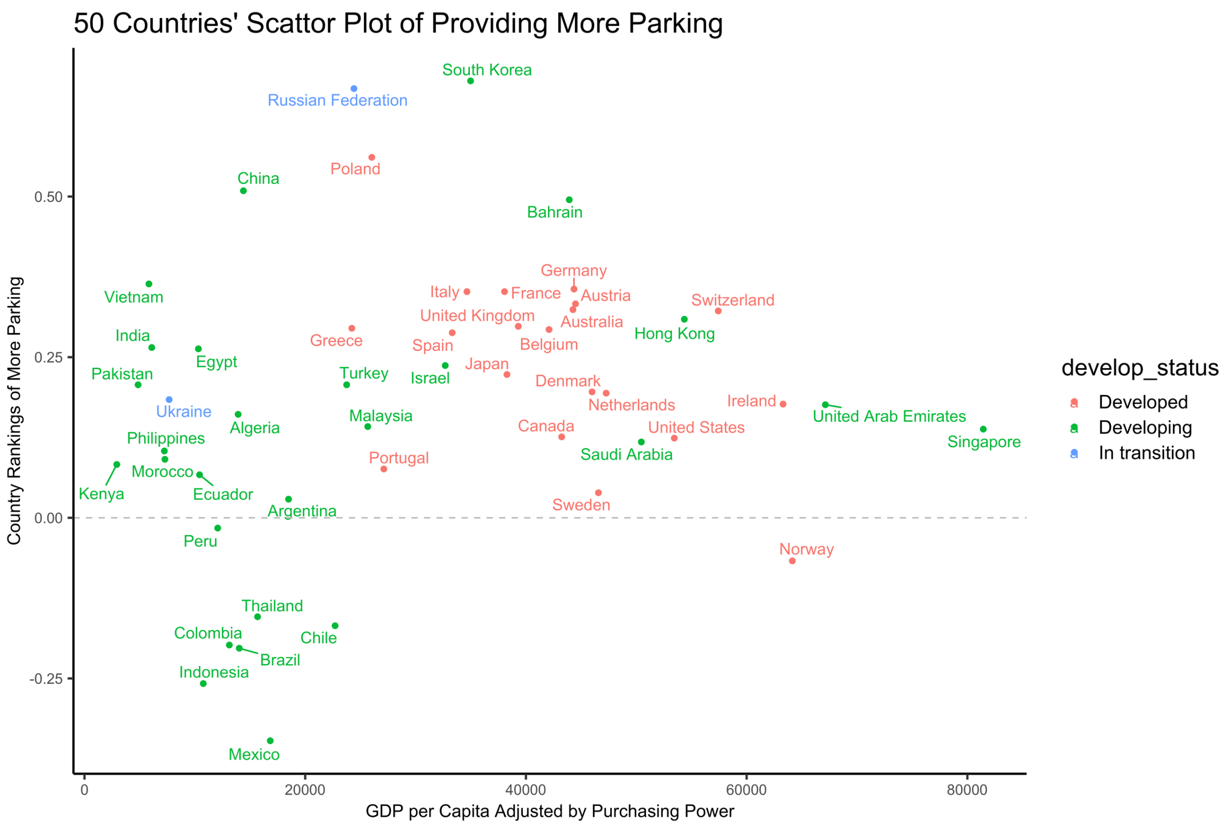
Figure 5.5 50 countries' scatter plot of supporting building additional roads, vs. GPD per capita of 2016, adjusted by purchasing power parity



In Figure 5.5 developing countries are colored in green, developed countries are in red, and the two countries "in transition" (Ukraine and Russia) are in blue. Developing countries scatter on the left half of the graph, as developing countries have lower GDP per capita compared to developed countries. For developing countries, higher GDP per capita leads to less support on the policy of building additional roads. On the other hand, developed countries tend to have less support on this road policy, besides Poland, which is higher than the rest of the developed countries and even most of the developing countries.

GDP per capita is also negatively correlated with national level support on providing more pedestrian facilities in all types of countries (see Table 5.2). But for most policies, for example, providing more parking, the correlation with GDP per capita is not strong overall. The scatter plot Figure 5.6 implies that both developing and developed countries have positive support on more parking. Being in almost any of the developed countries would result in a positive gain on supporting more parking provision; but the level of support can be similar in many of the developing countries as well. While for developed countries, the relation between support on more parking and GDP per capita is negative, indicating that higher GDP per capita correlates with low support on parking. However, this trend does not preserve and is less obvious for developing countries and all 50 countries as a whole.

Figure 5.6 50 countries' scatter plot of providing more parking, vs. GPD per capita of 2016, adjusted by purchasing power parity



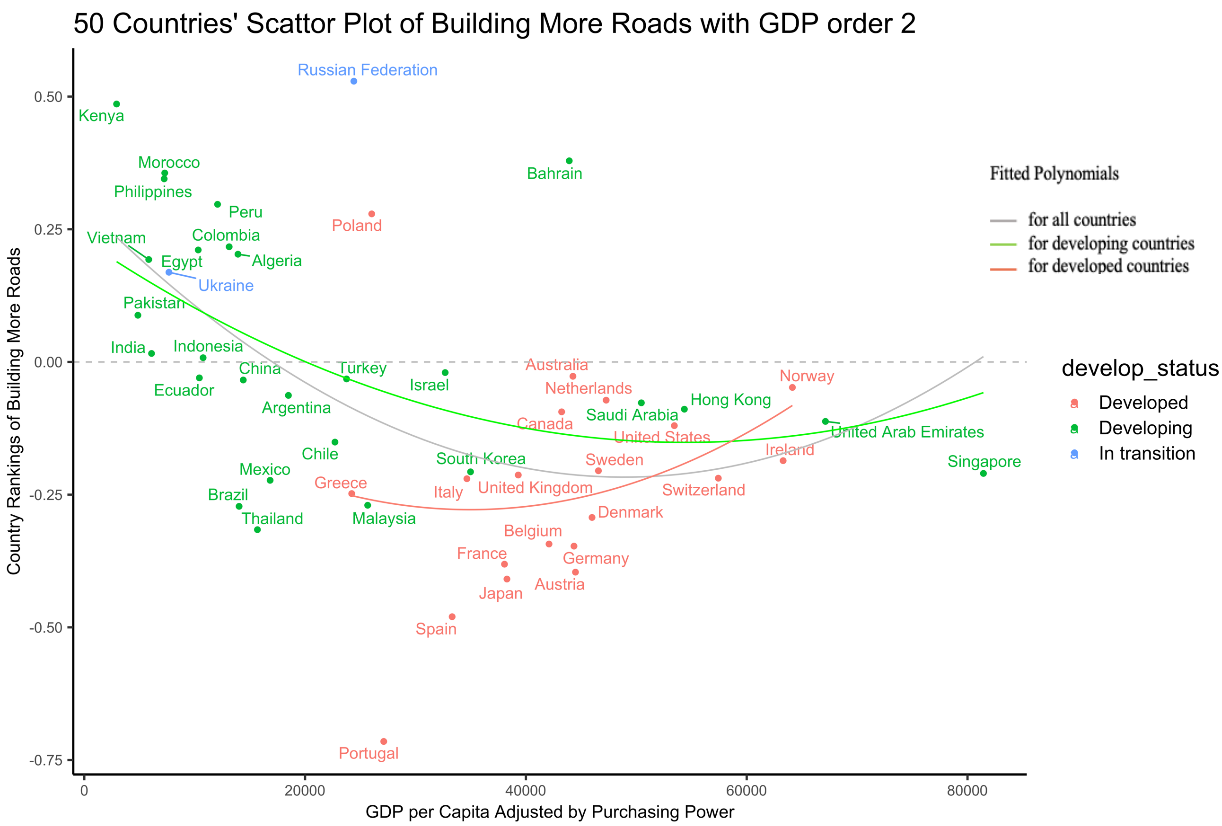
A more detailed modeling approach can be taken if one is interested in knowing the trajectory and turning point of development phases given by country factors. For example, given that in Figure 5.5, the country ranking score on building additional roads seems to be correlated with GDP per capita. I built simple linear regression model using 50 country rankings with respect to their GDP per capita, adjusted by the purchasing power parity in 2016. I also included the square of GDP per capita, trying to capture the non-linear relation between support on building additional roads and GDP. The statistics in Table 5.3 of the model (support of more roads ~ GDP + GDP ^2) returns a negative coefficient for GDP and positive coefficient for GDP squared.

Table 5.3 Linear model of country-level support on building additional road with respect to GDP per capita and GDP per capita squared.

	Estimates	P value	Significance
Intercept	2.944 e-01	0.002245	**
GDP	-2.092e-05	0.000825	***
GDP 2	2.141e-10	0.010002	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Adjusted R-squared: 0.2672.

Figure 5.7 50 countries' scatter plot of supporting providing more roads, with respect to DGP per capita.

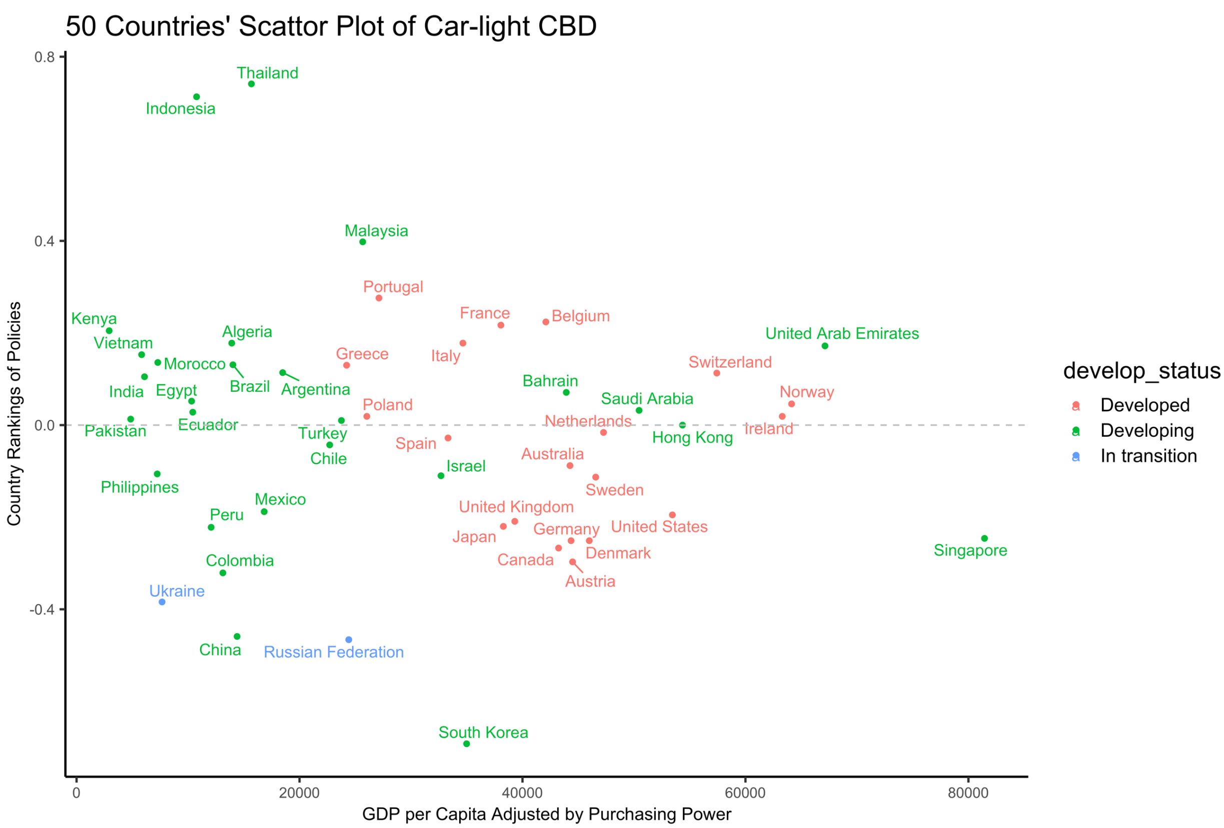


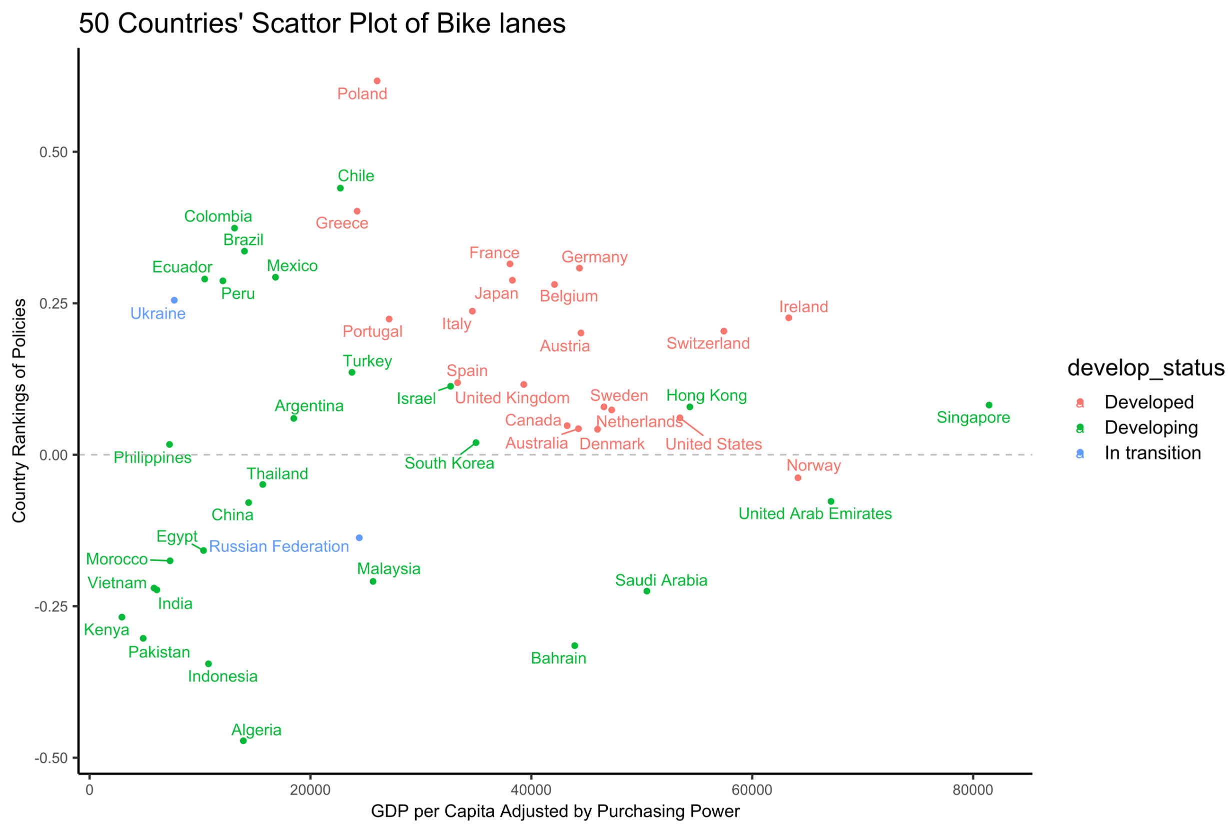
A polynomial (order 2) curve is added to illustrate the relation ("U" shape) between countries' GDP per capita and country scores on supporting building more roads. Most developing countries follow the first half of the U shape: when countries are at the very low end of GDP per capita, these countries prioritize road infrastructure considerately. But when countries evolve and enter the era of having higher GDP per capita, their prioritization of transportation policies can pivot to other items, and the demand decreases with lower rate (flattens) over time. The salmon-color-curve fitted for the developed countries only indicates that there is no obvious descending part of the trend and the curve is flatter compared to that of developing countries and all countries.

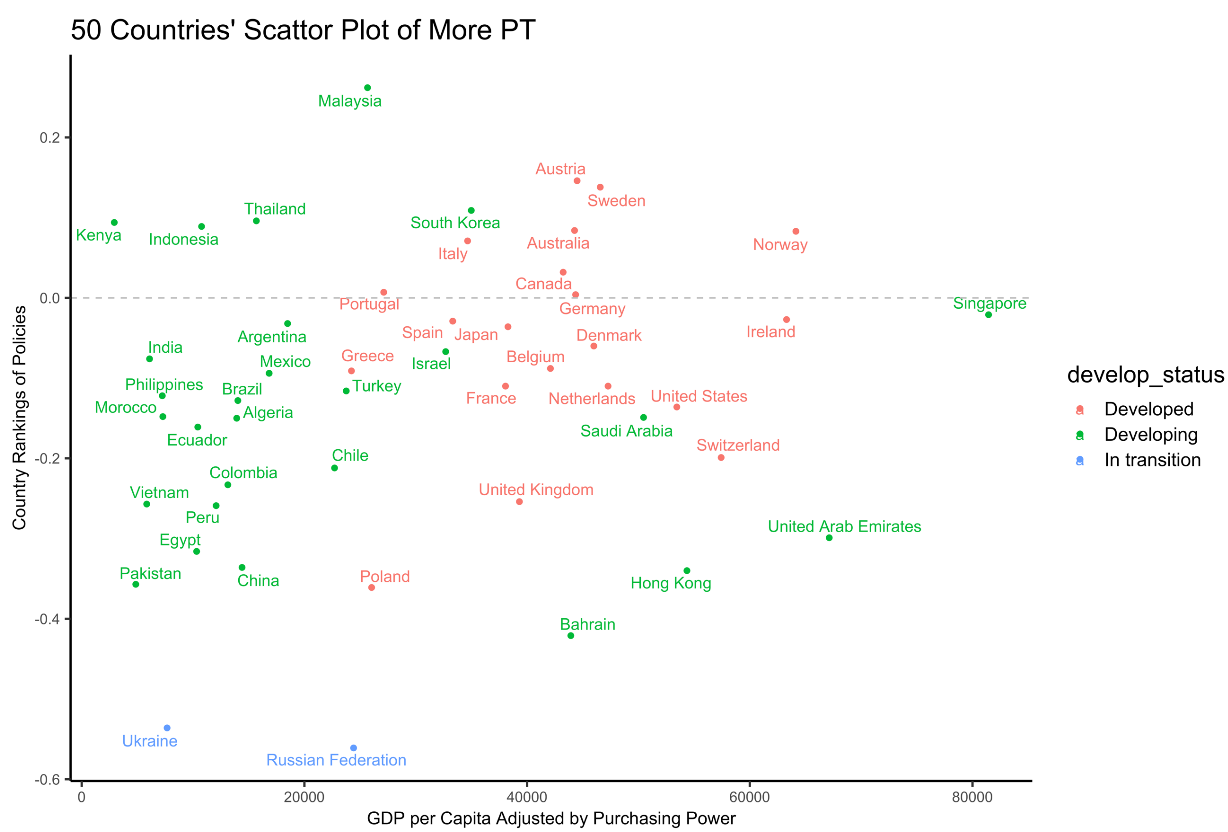
Due to the limitation of the data size that only 50 countries' scores are available, building out a complex model by including multiple variables to detangle country-level variance would result in small degree of freedom. Another way to study the country-level factors is using multi-level SEM, so that country-level coefficients are estimated simultaneously with individual-level coefficients, if the size of clusters are appropriately large enough.

For the sake of comprehensiveness of showing all the 11 policies' country ranking with respect to the important factor—GDP per capita—I will present all the scatter plots below in Figure 5.8. Readers may find some patterns interesting to explore further.

Figure 5.8 Country-level support on policies other than pro-car's policies.




50 Countries' Scattor Plot of Bike lanes
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
develop_status
Developed
Developing
In transition
Poland
Chile
Colombia
Greece
Brazil
Ecuador
Mexico
Peru
Ukraine
France
Germany
Japan
Belgium
Italy
Ireland
Portugal
Austria
Switzerland
Turkey
Spain
Israel
United Kingdom
Sweden
Hong Kong
Argentina
Canada
Netherlands
Singapore
Australia
Denmark
United States
Philippines
South Korea
Norway
Thailand
China
United Arab Emirates
Egypt
Russian Federation
Morocco
Malaysia
Vietnam
Saudi Arabia
India
Kenya
Pakistan
Bahrain
Indonesia
Algeria


50 Countries' Scattor Plot of More PT
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
develop_status
Developed
Developing
In transition
Malaysia
Austria
Sweden
Thailand
South Korea
Kenya
Indonesia
Italy
Australia
Norway
Canada
Portugal
Germany
Singapore
Spain
Japan
Ireland
India
Argentina
Denmark
Greece
Israel
Belgium
Mexico
Philippines
Brazil
Turkey
France
Netherlands
United States
Morocco
Algeria
Saudi Arabia
Ecuador
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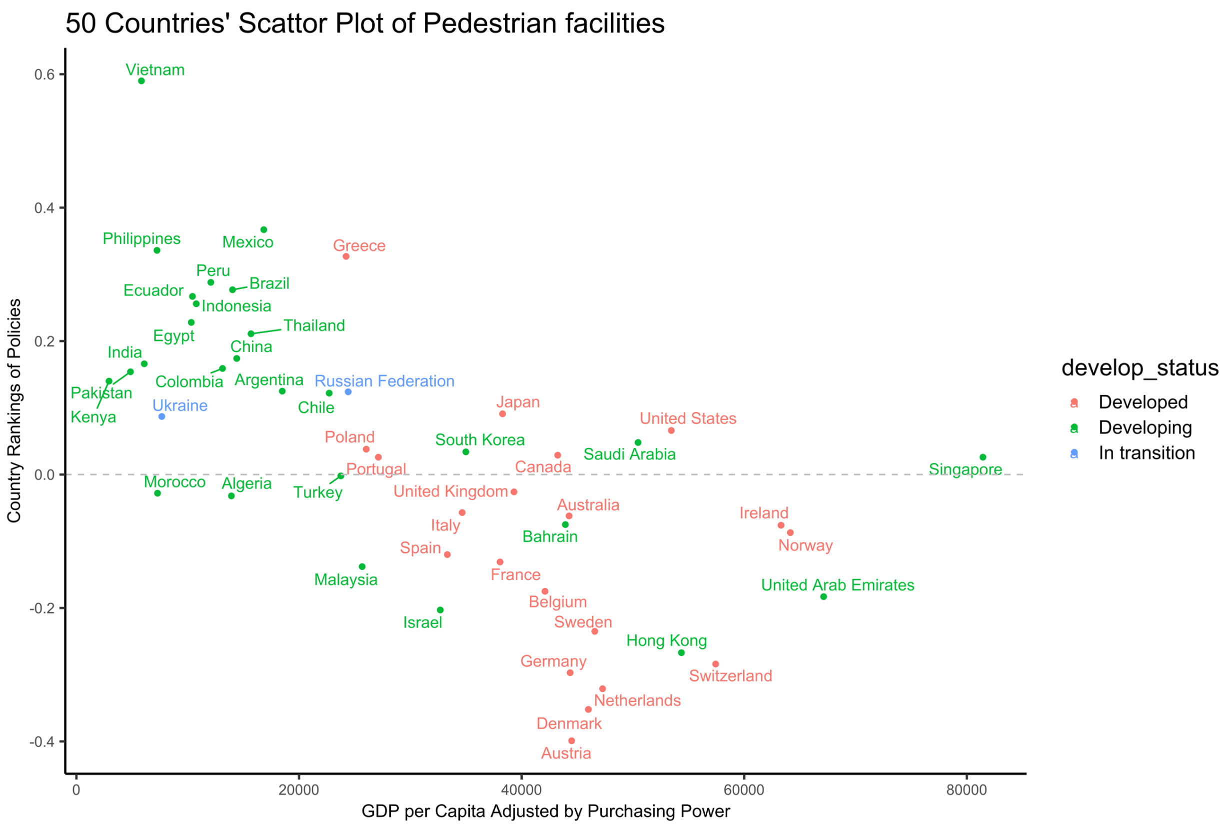
Hong Kong
Bahrain
Ukraine
Russian Federation


50 Countries' Scattor Plot of Pedestrian facilities
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
0.6
0.4
0.2
0.0
-0.2
-0.4
0
20000
40000
60000
80000
Vietnam
Philippines
Mexico
Greece
Peru
Ecuador
Brazil
Indonesia
Thailand
Egypt
China
India
Colombia
Argentina
Russian Federation
Pakistan
Ukraine
Chile
Kenya
Japan
United States
Poland
South Korea
Saudi Arabia
Portugal
Canada
Singapore
Morocco
Algeria
Turkey
United Kingdom
Australia
Ireland
Italy
Bahrain
Norway
Spain
Malaysia
France
United Arab Emirates
Belgium
Israel
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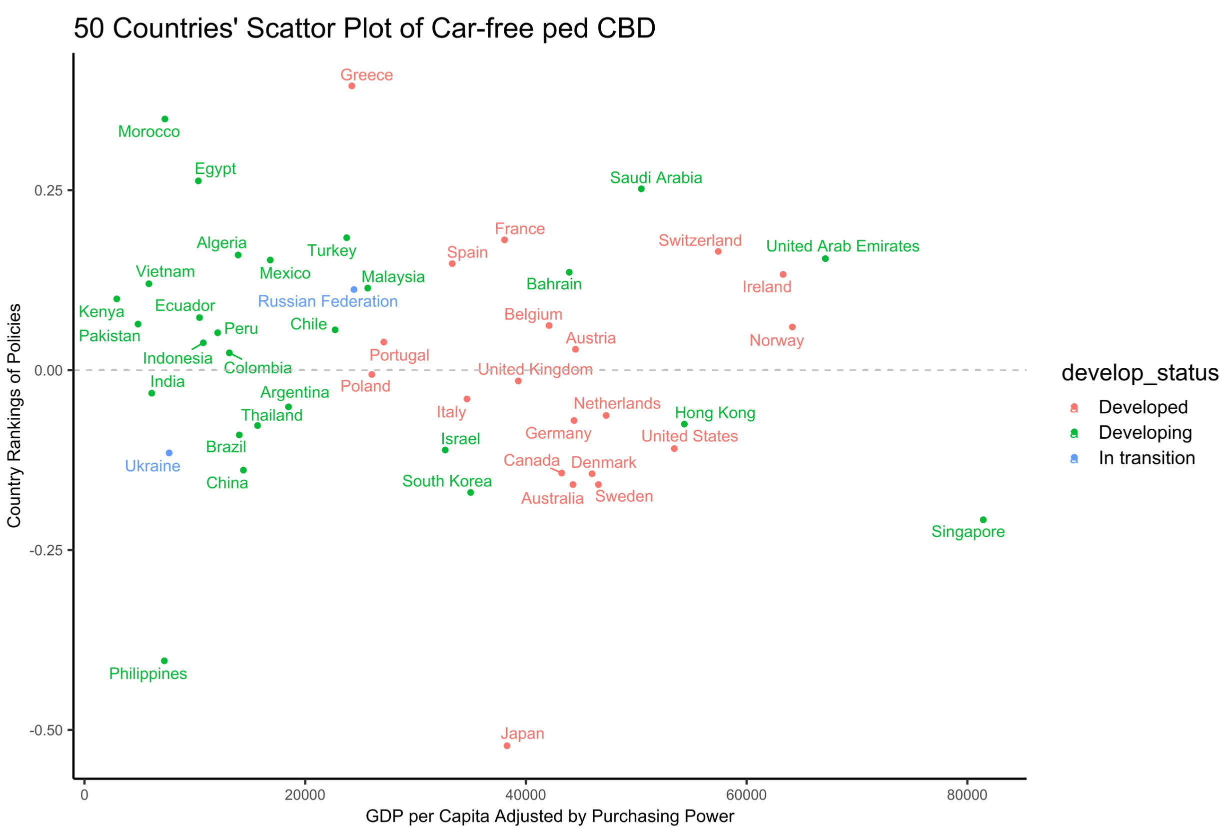
Germany
Switzerland
Netherlands
Denmark
Austria
develop_status
Developed
Developing
In transition


50 Countries' Scattor Plot of Car-free ped CBD
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
0.25
0.00
-0.25
-0.50
0
20000
40000
60000
80000
Greece
Morocco
Egypt
Saudi Arabia
France
Algeria
Turkey
Spain
Switzerland
United Arab Emirates
Vietnam
Mexico
Malaysia
Bahrain
Ireland
Kenya
Ecuador
Russian Federation
Belgium
Pakistan
Peru
Chile
Norway
Austria
Indonesia
Portugal
Colombia
United Kingdom
India
Argentina
Poland
Netherlands
Thailand
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Israel
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Sweden
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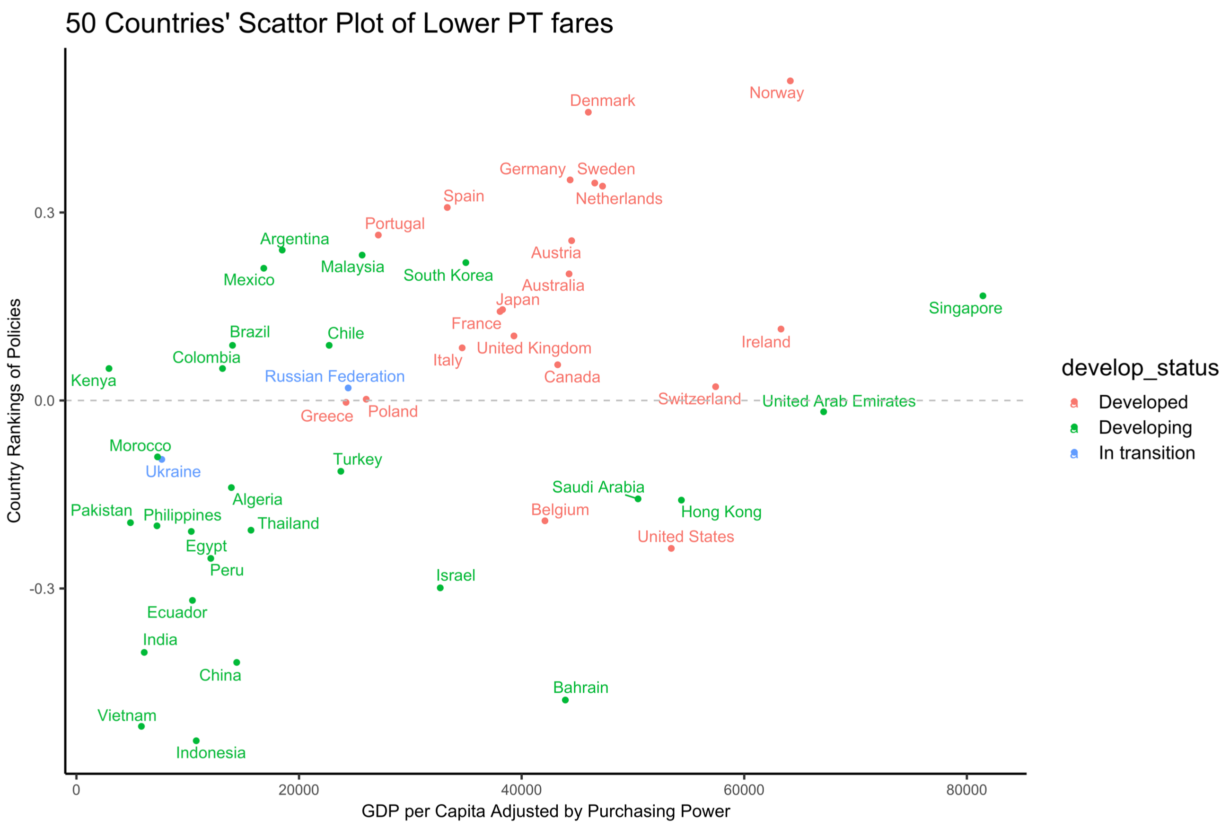
Philippines
Japan
develop_status
Developed
Developing
In transition


50 Countries' Scattor Plot of Lower PT fares
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
0.3
0.0
-0.3
0
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40000
60000
80000
Norway
Denmark
Germany
Sweden
Netherlands
Spain
Portugal
Argentina
Malaysia
Mexico
South Korea
Austria
Australia
Japan
Singapore
France
Ireland
Brazil
Chile
United Kingdom
Italy
Colombia
Canada
Kenya
Russian Federation
Switzerland
United Arab Emirates
Greece
Poland
Morocco
Ukraine
Turkey
Saudi Arabia
Algeria
Hong Kong
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Philippines
Belgium
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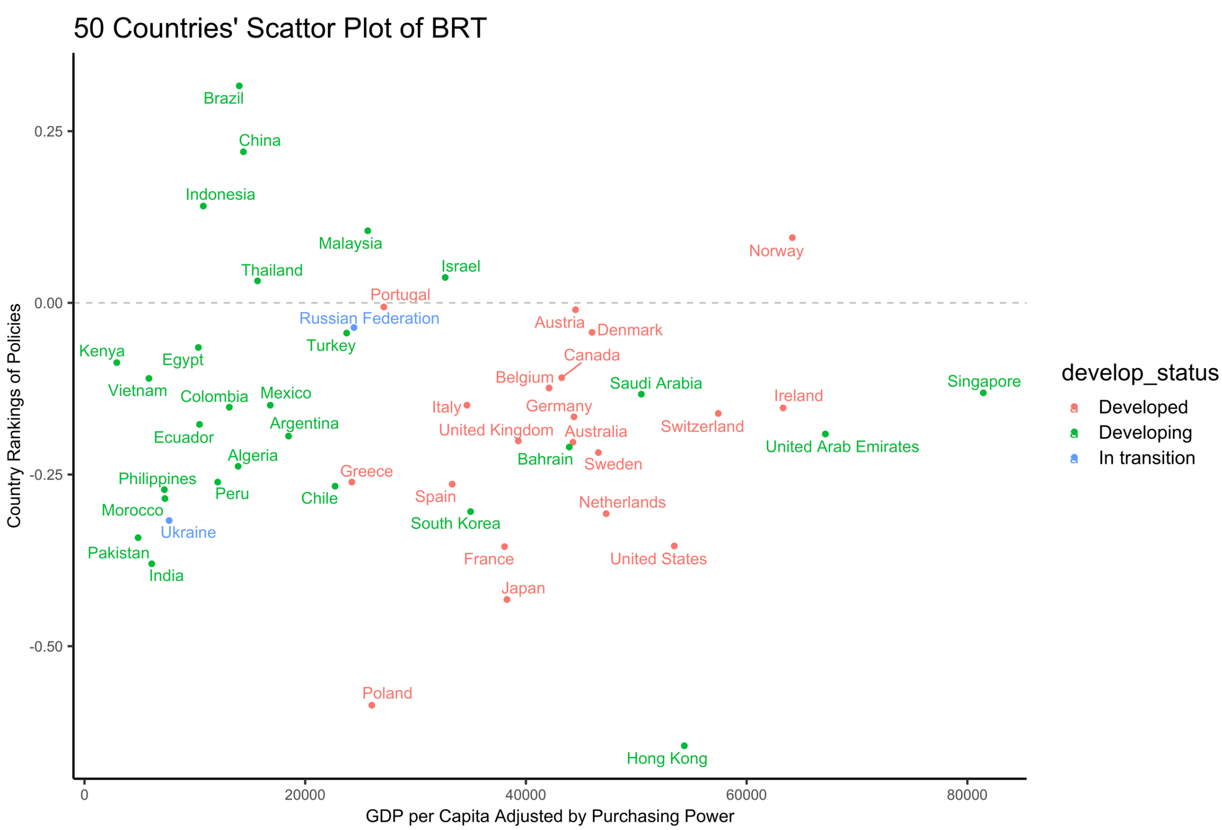
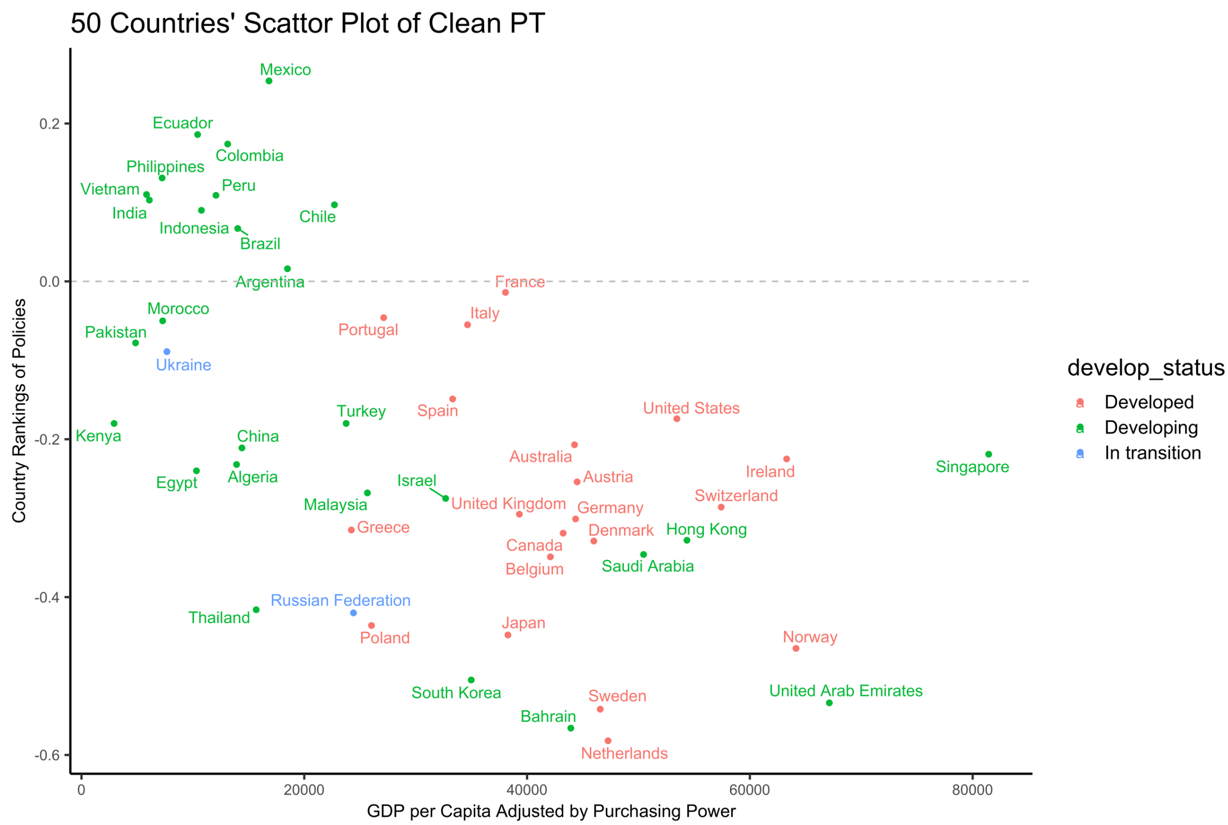
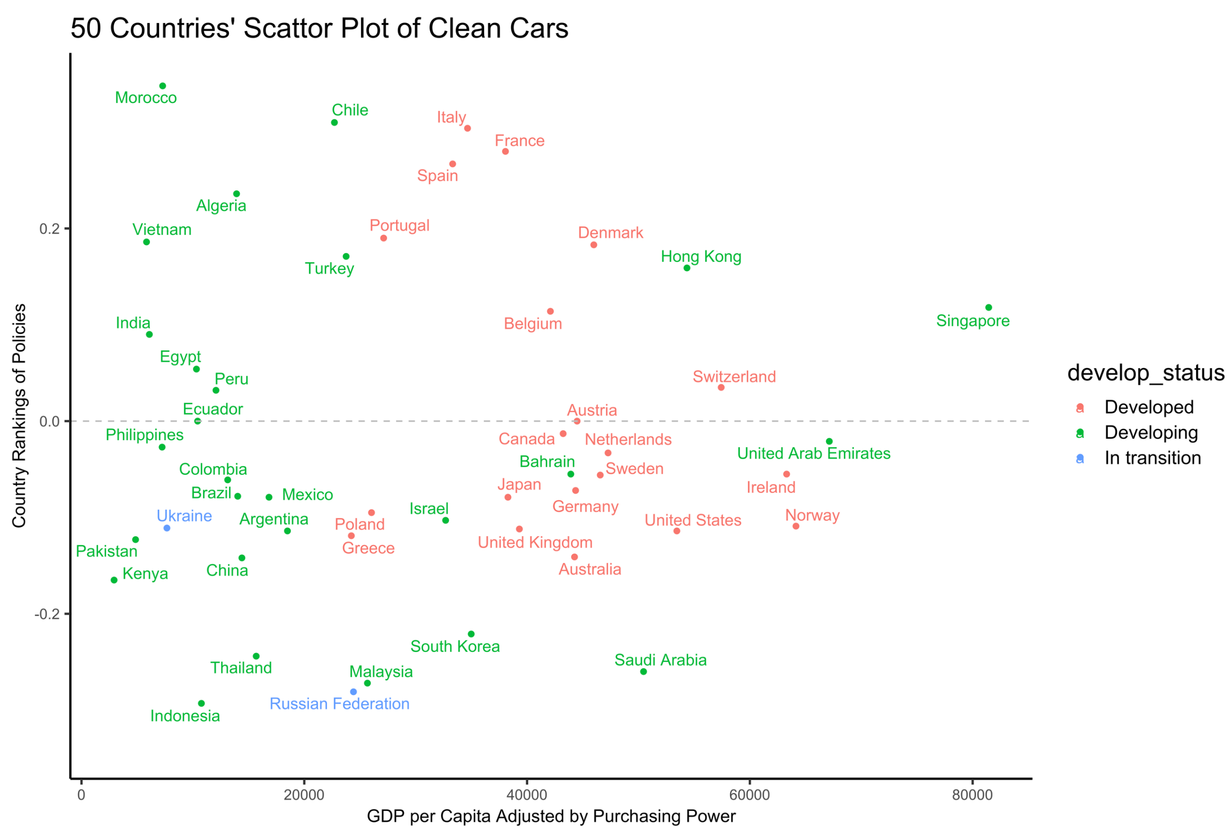
India
China
Bahrain
Vietnam
Indonesia
develop_status
Developed
Developing
In transition


50 Countries' Scattor Plot of BRT
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
0.25
0.00
-0.25
-0.50
0
20000
40000
60000
80000
Brazil
China
Indonesia
Malaysia
Norway
Thailand
Israel
Portugal
Russian Federation
Austria
Denmark
Kenya
Egypt
Turkey
Canada
Belgium
Saudi Arabia
Singapore
Vietnam
Colombia
Mexico
Italy
Germany
Ireland
Ecuador
Argentina
United Kingdom
Australia
Switzerland
United Arab Emirates
Algeria
Bahrain
Sweden
Philippines
Greece
Peru
Chile
Spain
Morocco
Netherlands
Ukraine
South Korea
Pakistan
France
United States
India
Japan
Poland
Hong Kong
develop_status
Developed
Developing
In transition


50 Countries' Scattor Plot of Clean PT
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
develop_status
Developed
Developing
In transition
Mexico
Ecuador
Colombia
Philippines
Vietnam
India
Peru
Chile
Indonesia
Brazil
Argentina
France
Italy
Portugal
Morocco
Pakistan
Ukraine
Turkey
Spain
United States
Kenya
China
Australia
Ireland
Singapore
Egypt
Algeria
Israel
Austria
Malaysia
United Kingdom
Switzerland
Germany
Greece
Denmark
Hong Kong
Canada
Belgium
Saudi Arabia
Russian Federation
Thailand
Poland
Japan
Norway
South Korea
Sweden
United Arab Emirates
Bahrain
Netherlands


50 Countries' Scattor Plot of Clean Cars
Country Rankings of Policies
GDP per Capita Adjusted by Purchasing Power
develop_status
Developed
Developing
In transition
Morocco
Chile
Italy
France
Spain
Algeria
Vietnam
Portugal
Denmark
Hong Kong
Turkey
Belgium
Singapore
India
Egypt
Peru
Switzerland
Ecuador
Austria
Philippines
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United Arab Emirates
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Argentina
Israel
Poland
United States
Norway
Greece
United Kingdom
Pakistan
Kenya
China
Australia
South Korea
Saudi Arabia
Thailand
Malaysia
Russian Federation
Indonesia

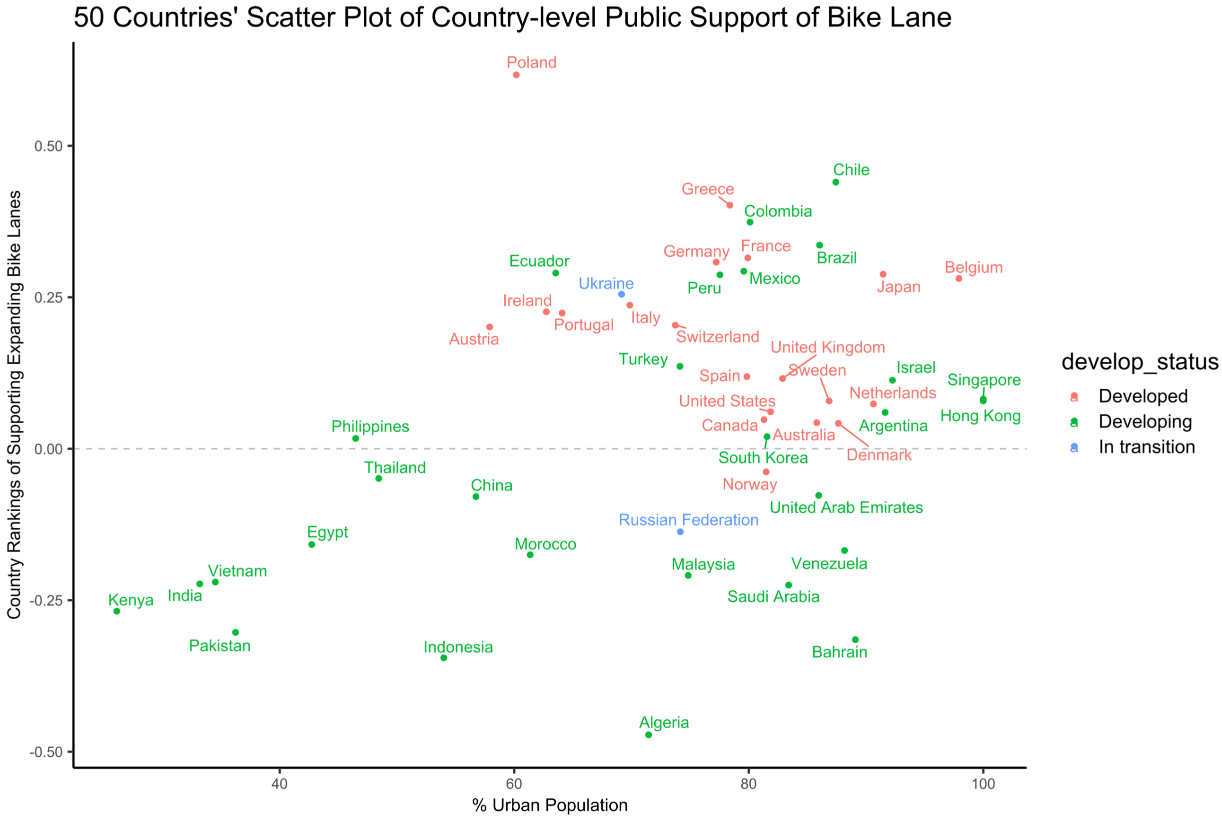
5.2.2 Passenger Kilometers per Capita

Passenger kilometers per capita has similar pattern as GDP per capita, possibly also because the two factors correlate strongly from Table 5.2. Notably, number of registered vehicles per capita positively correlates with support on expanding bike lanes for all countries, with support on expanding public transportation services for all and developing countries and with support on prioritizing BRT in developing countries. This indicates that high vehicle ownership can correlate with public support on alternative modes.

5.2.3 Urban Population

The factor of percentage of population in urban area has positive correlation on expanding bike lanes. This factor could possibly be interpreted as urbanization rate. The finding is that with more population in urban area, it is more likely to witness high country-level support on expanding bike lanes. The scatter plot about country-level support on expanding bike lanes vs. percentage of population in urban area is shown in Figure 5.9. Hong Kong and Singapore have 100% of their population in urban area, because these two are city-states. Developed countries present a distinct pattern here, as almost all developed countries have positive ranking on the support of expanding bike lanes. That means, if a person is in developed countries, he/she would hold positive support toward expanding bike lane policies. But developed countries are not the only countries that support biking. Chile, Brazil, Mexico, Ecuador, etc. also have high rankings. By the correlation Table 5.2, we can tell that for all countries and especially developing countries, higher percentage of urban population nation-wide correlates with higher support on expanding bike lanes.

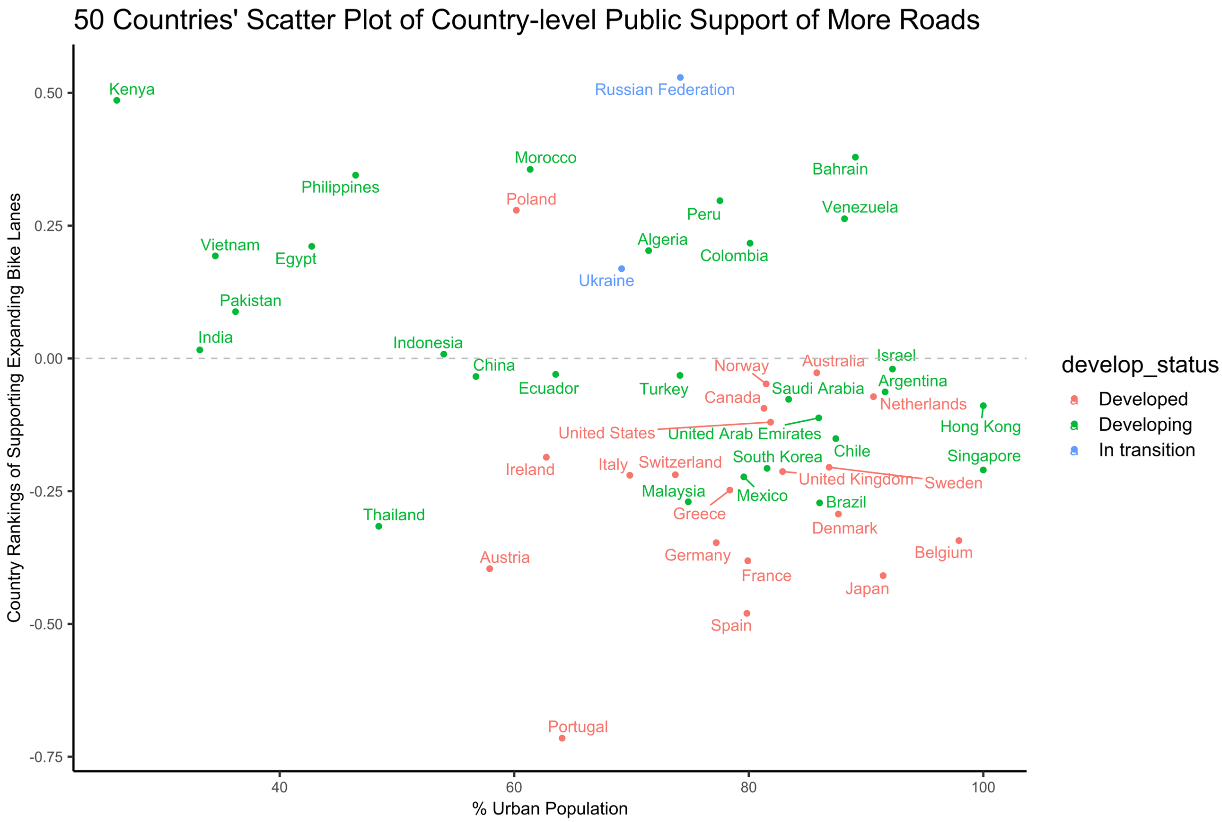
Figure 5.9 50 countries' scatter plot of support on expanding bike lanes, with respect to percentage of urban population.

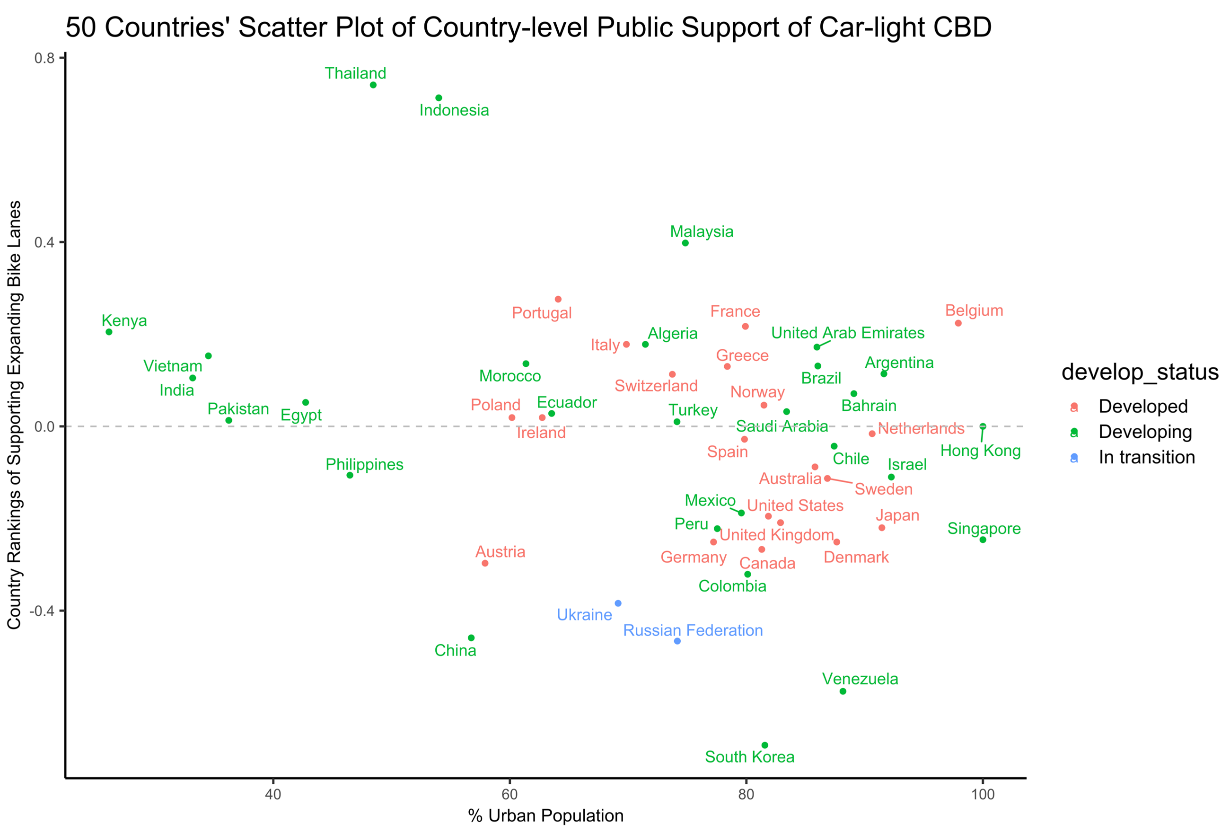


One country that behaves differently from its developed country peers is Poland. Poland seems to be an outlier in many scatter plots. One reasonable conclusion is that dropping this country out of the sample should change the correlation within developed countries. But the outlier is alerting that something special about Poland may exist; a zoom-in case study on this country may be helpful to understand the typology within developed countries.

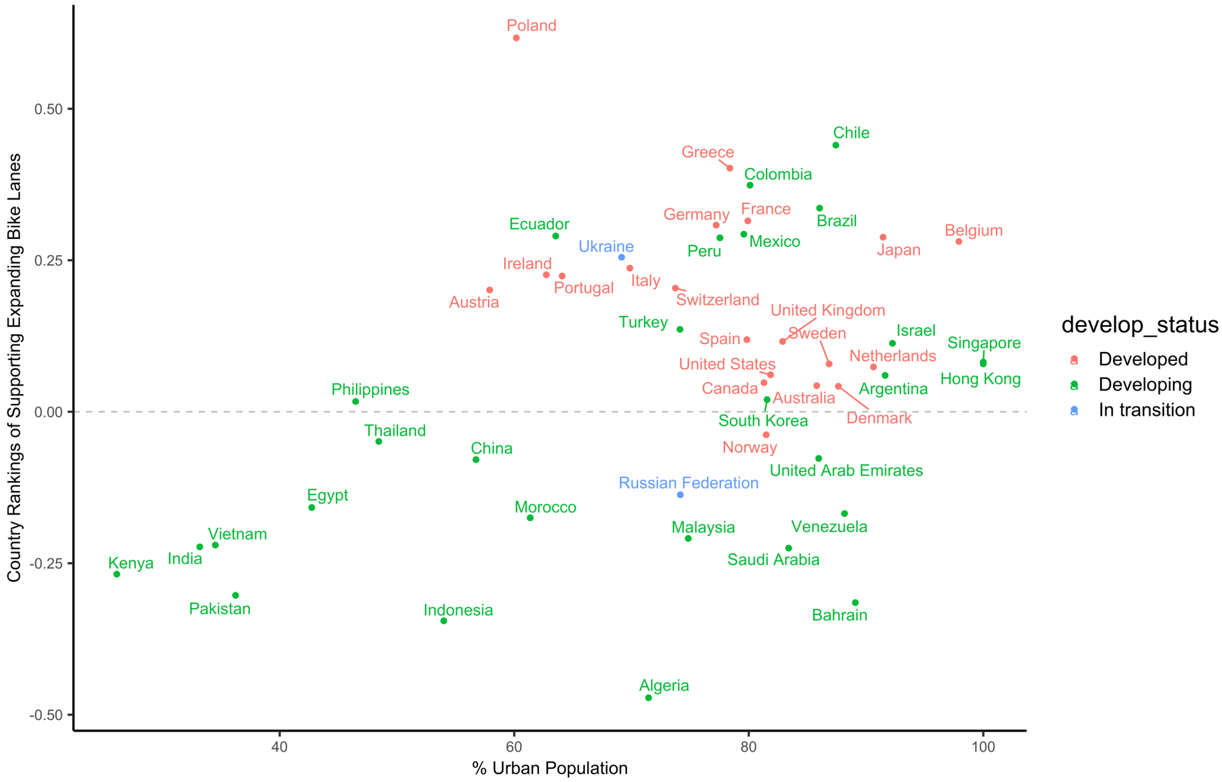
Similarly, scatter plots of other 10 policies will be provided below, in case readers are interested in certain policy items.

Figure 5.10 50 countries' scatter plot of support on 10 policies, with respect to percentage of urban population.

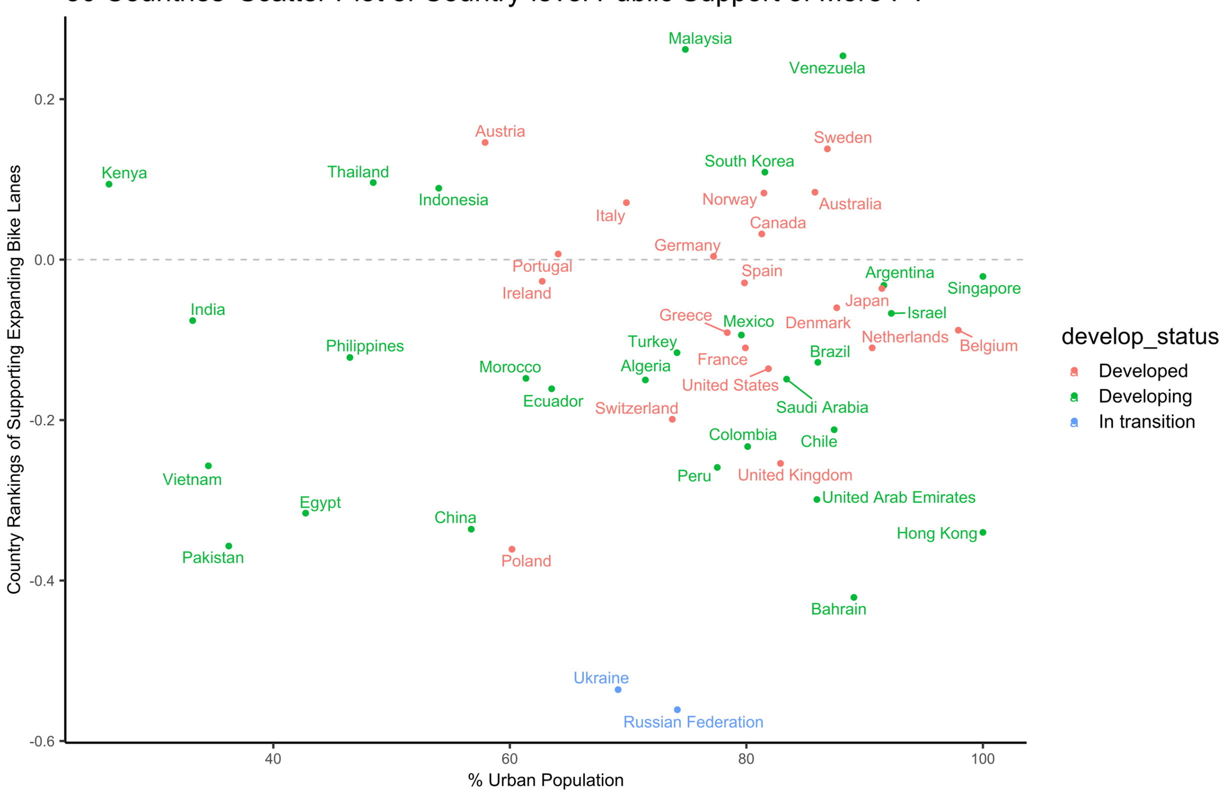




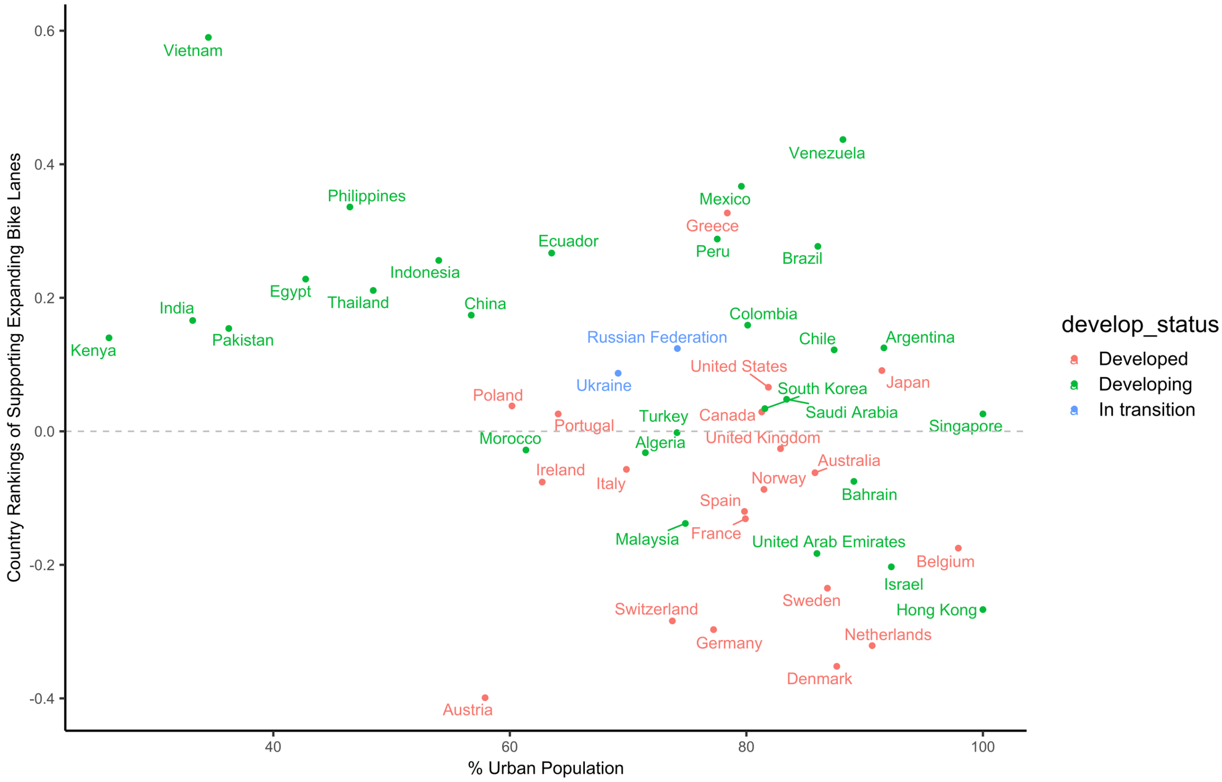
50 Countries' Scatter Plot of Country-level Public Support of Bike Lane



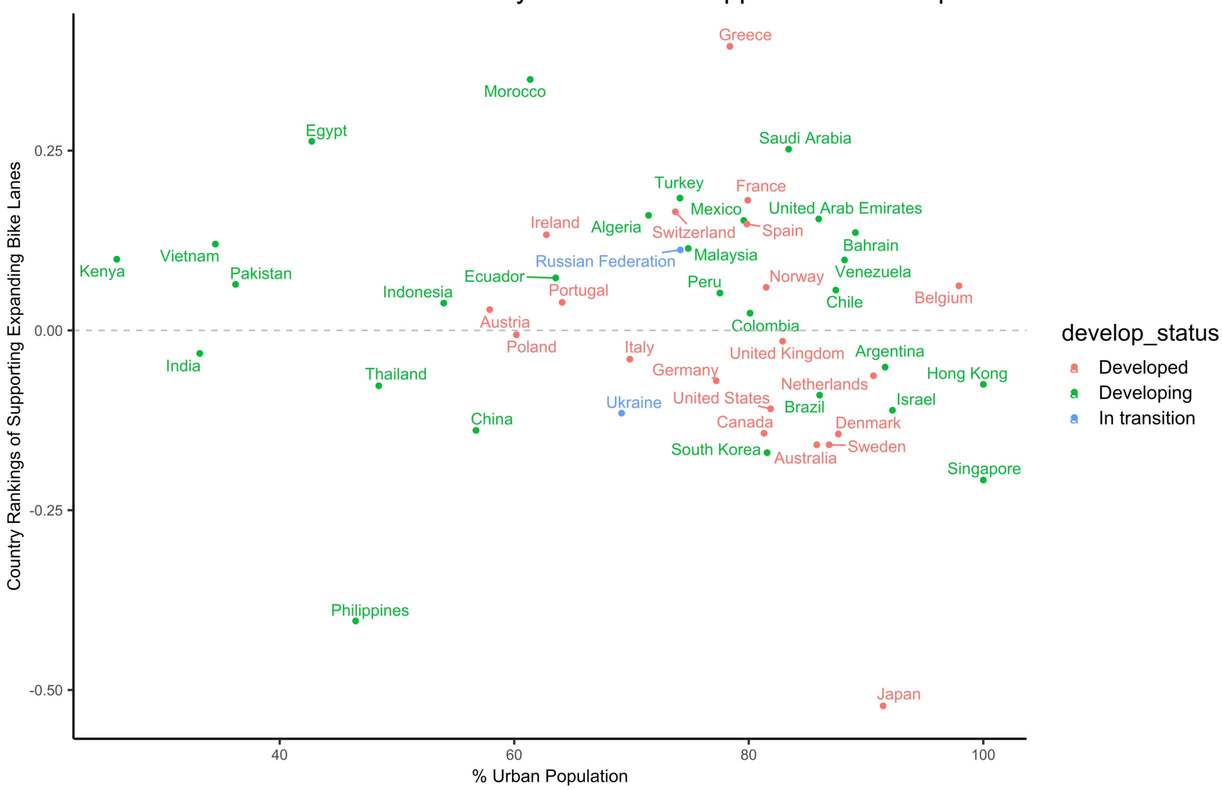
50 Countries' Scatter Plot of Country-level Public Support of More PT

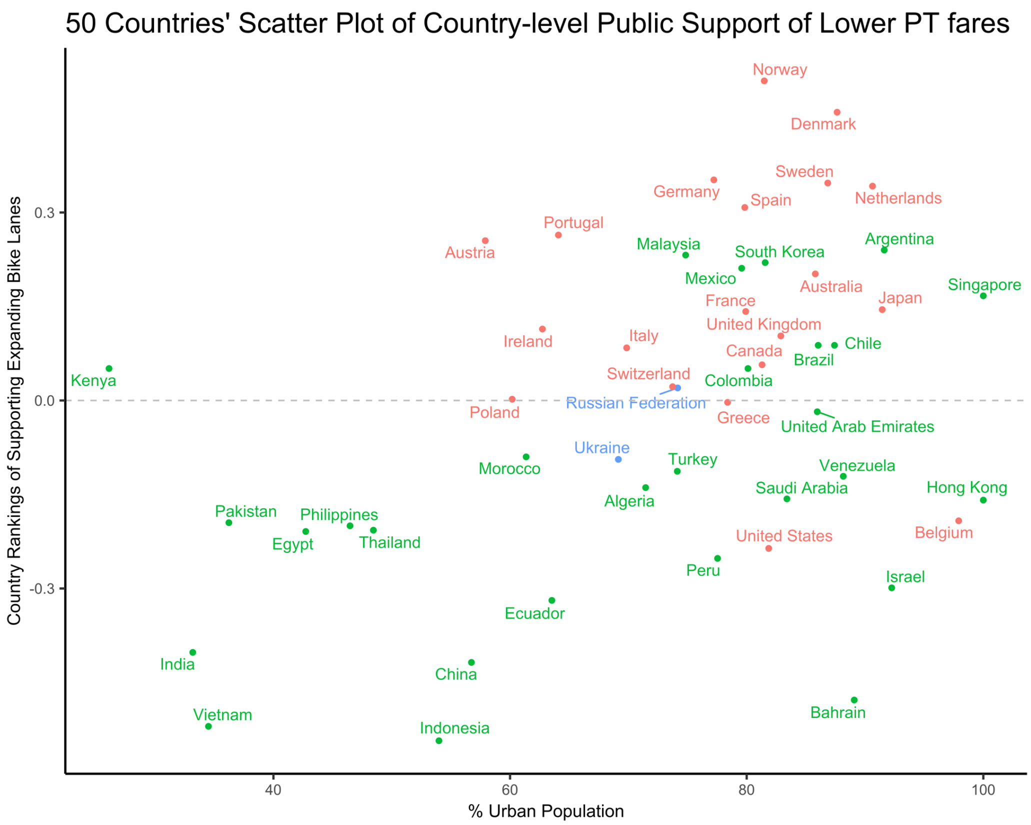


50 Countries' Scatter Plot of Country-level Public Support of Pedestrian facilities



50 Countries' Scatter Plot of Country-level Public Support of Car-free ped CBD




50 Countries' Scatter Plot of Country-level Public Support of Lower PT fares
Country Rankings of Supporting Expanding Bike Lanes
% Urban Population
develop_status
Developed
Developing
In transition
Norway
Denmark
Sweden
Germany
Spain
Netherlands
Portugal
Austria
Malaysia
South Korea
Argentina
Mexico
Australia
Singapore
France
Japan
United Kingdom
Ireland
Italy
Chile
Canada
Brazil
Kenya
Switzerland
Colombia
Russian Federation
Poland
Greece
United Arab Emirates
Ukraine
Turkey
Morocco
Venezuela
Saudi Arabia
Hong Kong
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Peru
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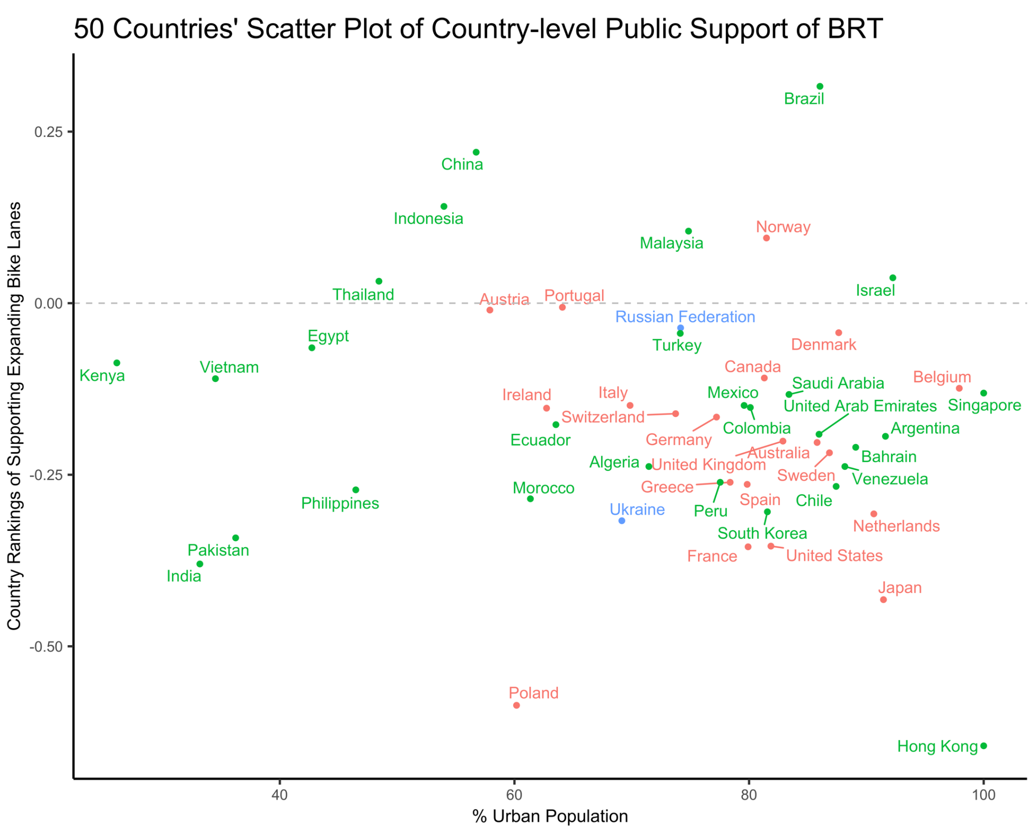
Ecuador
India
China
Bahrain
Vietnam
Indonesia


50 Countries' Scatter Plot of Country-level Public Support of BRT
Country Rankings of Supporting Expanding Bike Lanes
% Urban Population
develop_status
Developed
Developing
In transition
Brazil
China
Indonesia
Malaysia
Norway
Thailand
Austria
Portugal
Israel
Russian Federation
Egypt
Turkey
Denmark
Kenya
Vietnam
Canada
Saudi Arabia
Belgium
Ireland
Italy
Mexico
United Arab Emirates
Singapore
Switzerland
Colombia
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United Kingdom
Sweden
Venezuela
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United States
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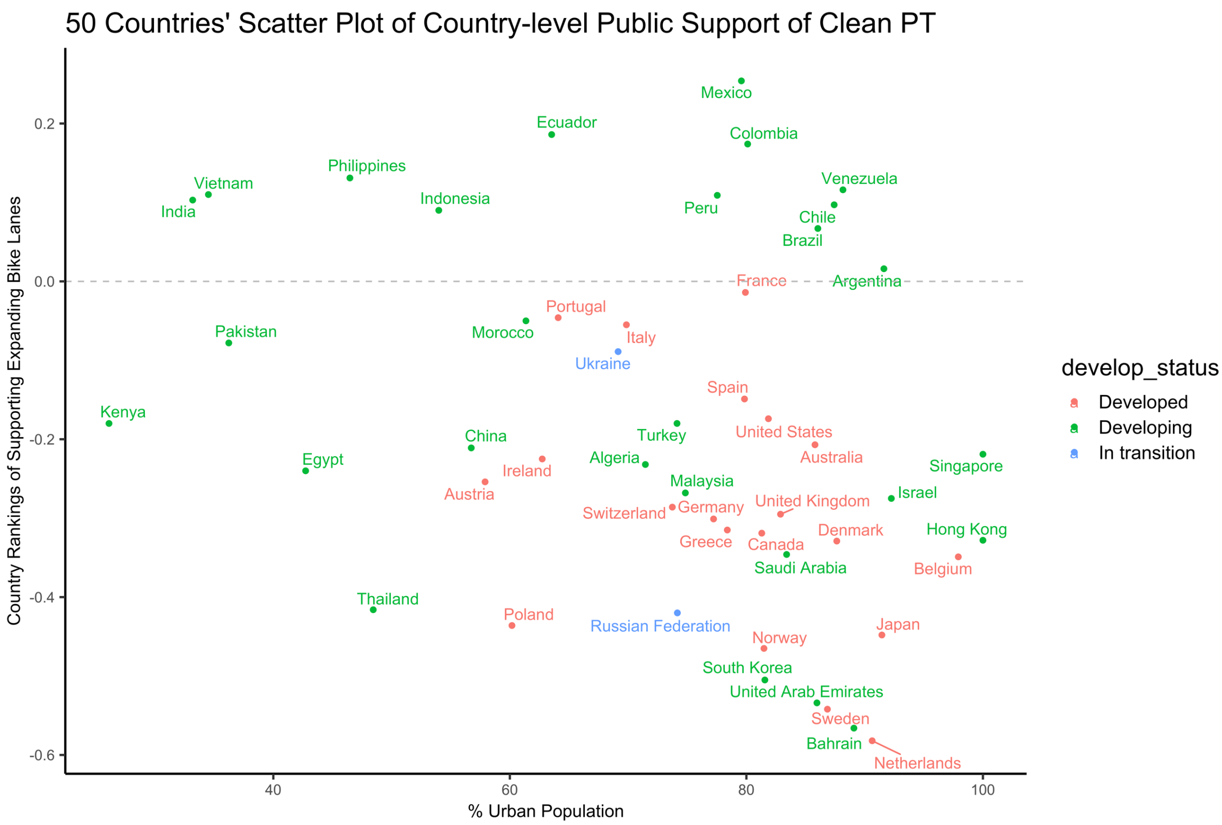
Poland
Hong Kong


50 Countries' Scatter Plot of Country-level Public Support of Clean PT
Country Rankings of Supporting Expanding Bike Lanes
% Urban Population
0.2
0.0
-0.2
-0.4
-0.6
40
60
80
100
develop_status
Developed
Developing
In transition
Mexico
Ecuador
Colombia
Philippines
Vietnam
India
Indonesia
Venezuela
Peru
Chile
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France
Argentina
Portugal
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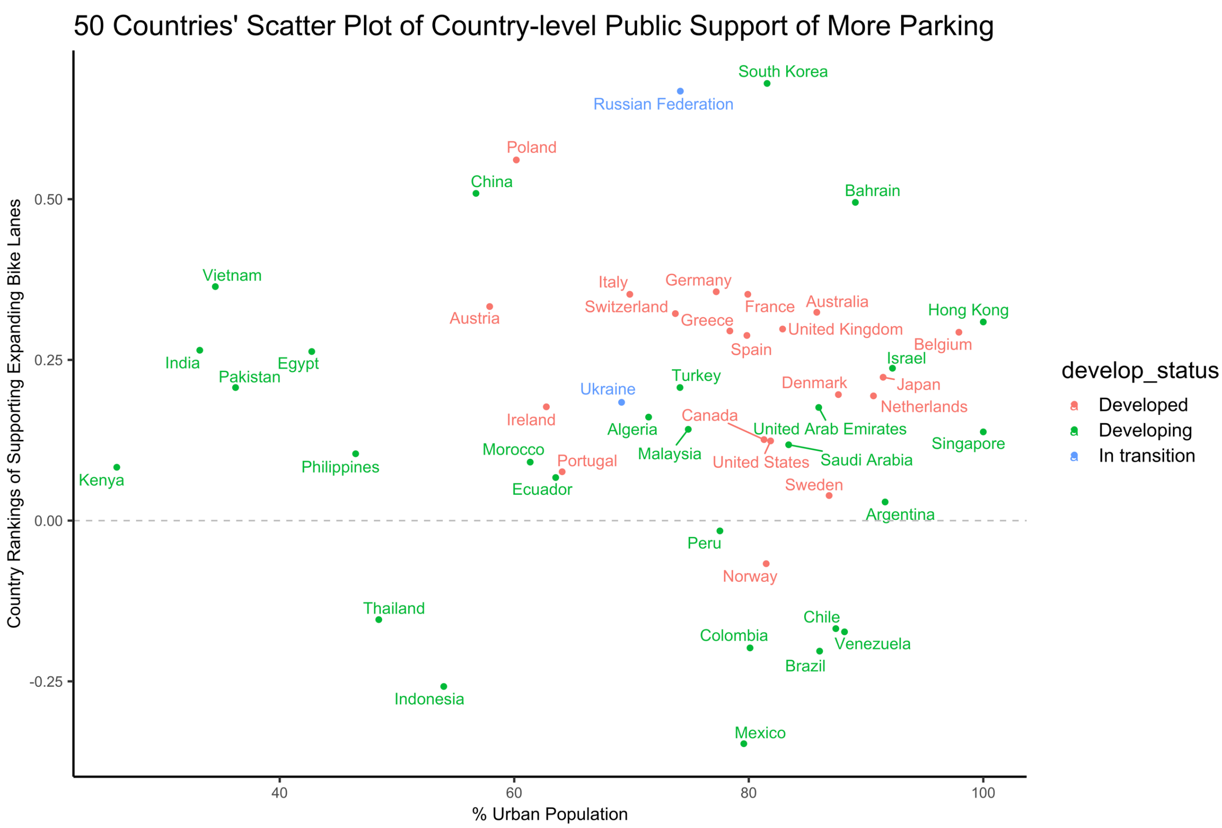
Netherlands


50 Countries' Scatter Plot of Country-level Public Support of More Parking
Country Rankings of Supporting Expanding Bike Lanes
% Urban Population
0.50
0.25
0.00
-0.25
40
60
80
100
develop_status
Developed
Developing
In transition
South Korea
Russian Federation
Poland
China
Bahrain
Vietnam
Italy
Germany
Switzerland
France
Australia
Austria
Greece
Hong Kong
United Kingdom
Belgium
India
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Saudi Arabia
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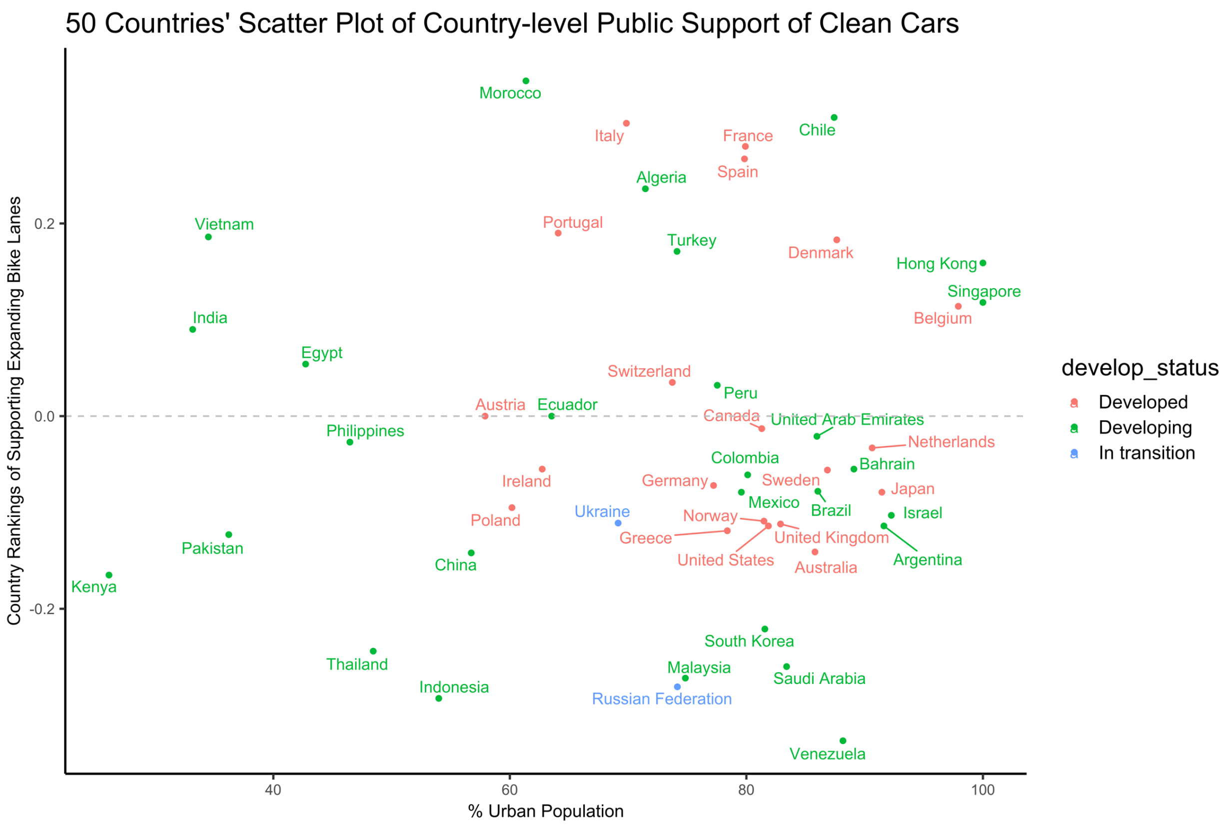
Venezuela
Brazil
Indonesia
Mexico



5.3 Country Clusters

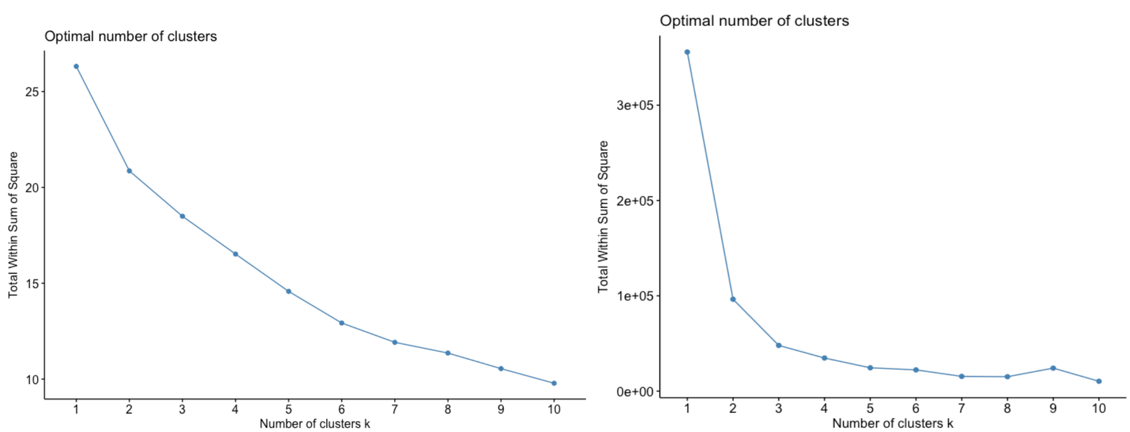
The 50 country by 11 policy matrix of country rankings allows us to focus on one policy and compare across countries, or to focus on one country and compare across policies. But the matrix does not make it easy to grasp a country's general policy support across all policies at a glance. For example, we may wonder how countries are similar or dissimilar in their patterns of policy support across all 11 policies.

We characterize countries based on their combinations or patterns of policy support using clustering analysis of the country ranking scores. The expected result can inform which countries are similar, which are dissimilar, and to what extent. By identifying the similarities and differences of country-level policy support, researchers and decision makers can better understand diverse approaches that entities in the globe choose to take, different development paths, and potential learning opportunities across countries if the nations share similar support across transportation policies.

5.3.1 Method

There are a few commonly used clustering methods, including k-means (that reduces the Euclidean distance of within-group sum of squares), Gaussian mixture algorithms (that reduces the standard deviation within groups) and hierarchical clustering. K-means is the most commonly used clustering method, as it is easy to understand and computationally tractable. It requires random initialization and input of number of clusters to proceed the clustering. To determine the right number of clusters for k-means, researchers often employ the elbow method, which finds the number of clusters so that adding another cluster doesn't improve much better the total within-cluster sum of square (WSS) (see k=3 in Figure 5.11 b). Ideally, the plot of WSS should have a tipping which gives the elbow shape, indicating at certain number of clusters, the trade-off between number of clusters and WSS is optimal. After this number of clusters, the within-group sum of square would still decrease, but of a much slower speed. However, k-means does not appear to work well with my data; the graph of WSS vs. the number of clusters returns continuing declining line without obvious slope change (see Figure 5.11 a).

Figure 5.11 Left (a): Total within-cluster sum of squares of my country-level ranking score by number of clusters, right (b): example of the ideal looking of total within-cluster sum of squares by number of clusters.



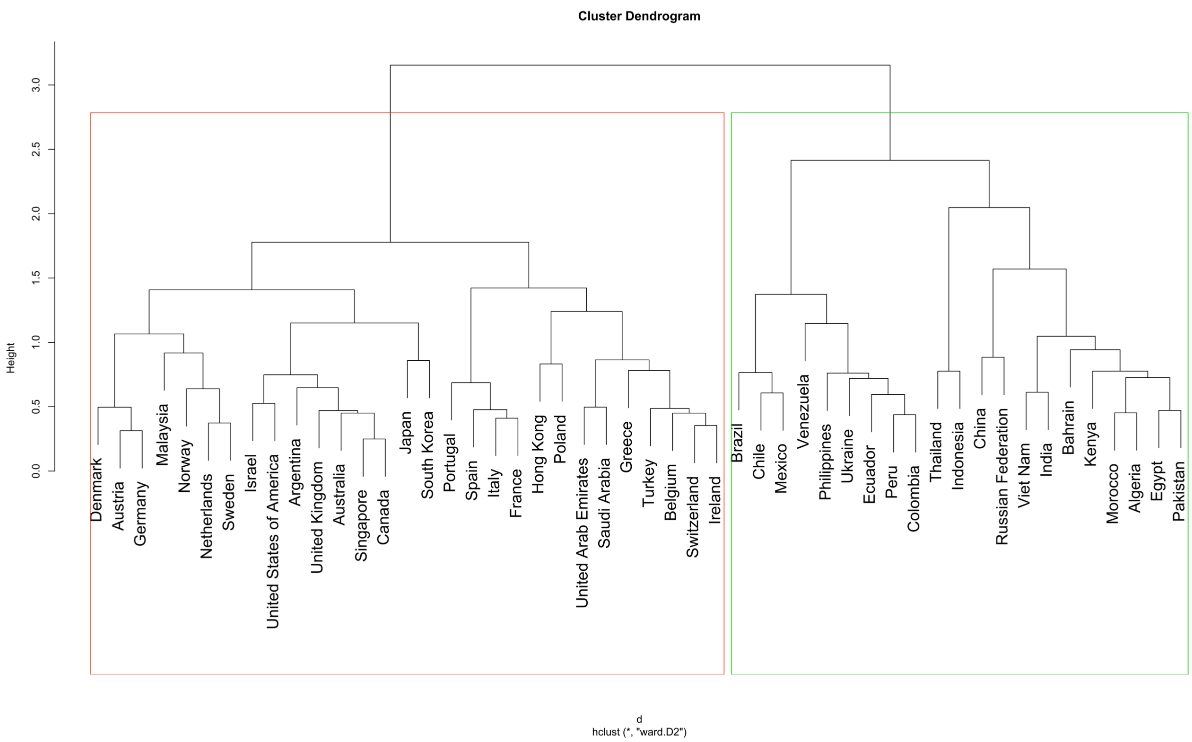
I also tried other diagnostics of k-means clustering, including Silhouette and Gap statistic (available in R package "fviz_nbclust") but none of them gave good results. K-means may not be the most appropriate method here because first, it tries to flatten the data while ignoring some of the nuances in multiple dimensions. Second, K-means tends to give clusters with similar size, which is not necessarily true in country clusters. Thus, I next tried hierarchical clustering. The strength of hierarchical clustering is that partitions can be visualized using a tree structure (or dendrogram), which helps view clusters at different levels of similarities. Also, it does not require a pre-identified number of clusters as input. The tree structure of hierarchical clustering allows the analyst to trace back through each step of the clustering algorithm to see how similar or dissimilar each endpoint is with respect to other clusters (Moody, 2016).

In hierarchical clustering, the merging or the division of clusters is performed according to a specified (dis)similarity measure. Agglomerative hierarchical clustering starts by treating each observation as a separate cluster. Then, two clusters that are most similar are identified and then fused into a new big cluster (DISPLAYR). One common way to measure the dissimilarity is by the Euclidean distance between each pair of observations. A number of different cluster agglomeration methods (Statistical Tools for High-Throughput Data Analysis) has been developed to measure the dissimilarity, including:

- Maximum or complete linkage clustering: It computes all pairwise dissimilarities between 2 clusters, and considers the largest distance between the two clusters.
- Minimum or single linkage clustering: It computes all pairwise dissimilarities between 2 clusters, and considers the shortest distance between the two clusters.
- Mean or average linkage clustering: It computes all pairwise dissimilarities between 2 clusters, and considers the average distances between the two clusters.
- Centroid linkage clustering: It computes the distance between the centroids of 2 clusters.
- Ward's minimum variance method: It minimizes the total within-cluster variance. At each step the pair of clusters with minimum between-cluster distance are merged.

In the following analysis, I choose to apply Ward's minimum variance method, which combines clusters whose combination results in the smallest increases in the overall within-cluster variance. Ward's minimum variance method aims at finding compact, spherical clusters. The results of the hierarchical clustering using Ward's method are shown in Figure 5.12.

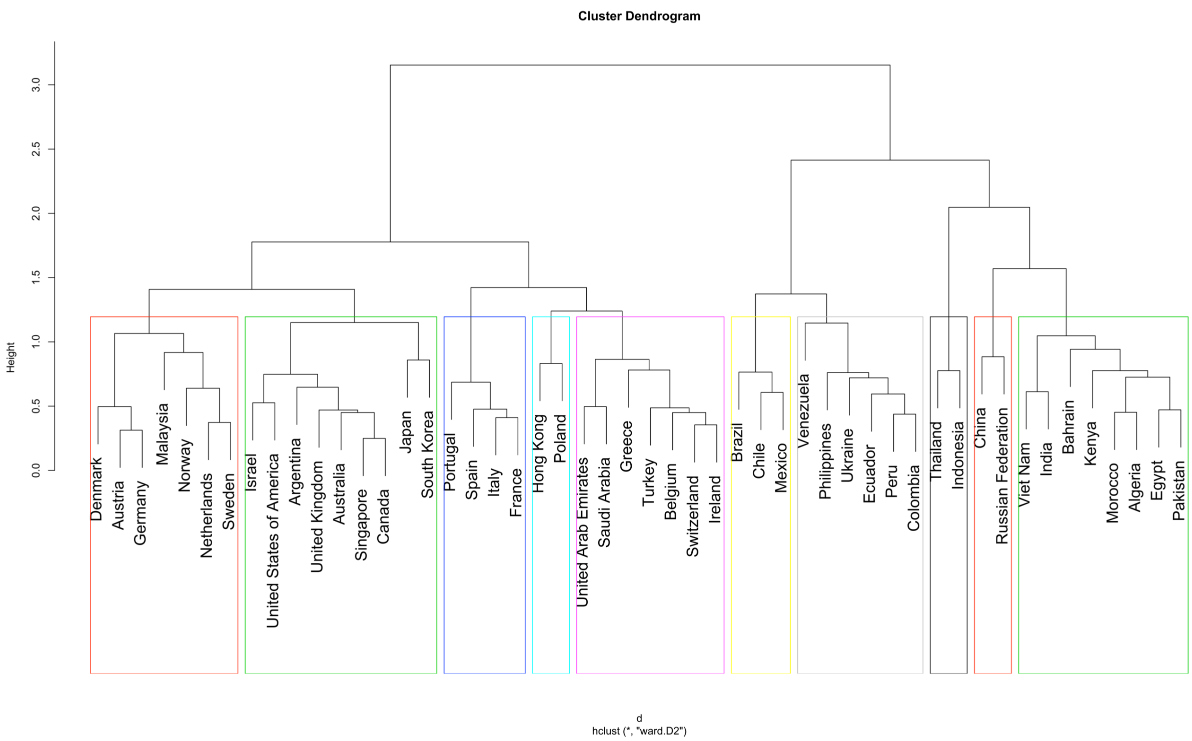
Figure 5.12 Hierarchical clustering, 2 clusters are produced.



The clustering tree in Figure 5.12 shows two clear clusters in the final merge, meaning that two distinct groups of countries exist until the last step. This largest distance roughly separates developed countries and the developing countries. Countries within the red color box on the left-hand side of Figure 5.12 are mostly developed countries, while countries within the green color box on the right-hand side are mostly developing countries. This finding suggests that what distinguishes countries most by their country-level coefficients of policy support across the 11 transportation policies is the status of being in a developing or developed country.

If we look earlier stages in the clustering merges, we can identify 10 clusters of countries that have similar characteristics (see Figure 5.13). There are three takeaway points we can discern here. First, countries with close geographic adjacency tend to share similar public support on transportation policies. For example, Nordic countries (like Denmark, Norway, Sweden, and the Netherlands) are clustered together with Germany and Austria (see the first red-color box on the far left). These countries all have good images about high share of public transit, biking and green modes of transport. But also, surprisingly it seems that Demark is closer to Germany and Austria, compared to Norway or Sweden.

Figure 5.13 Hierarchical clustering, 10 clusters are produced.



Italy, Spain, Portugal and France also share geographic adjacency (in the third block in blue). So do Japan and South Korea (in the second block in green). It is reasonable and natural that these countries share similar pattern on public support on transportation policies: neighboring countries possibly share similar climate conditions, geographical advantages or barriers, and development phases. Furthermore, because these countries are neighbors, opportunities for frequent cross-country dialogue also make the public opinions in their countries similar.

While many clusters show geographic adjacency, some clusters include countries that are physically separated. In the second green block, Singapore and Canada are clustered together from the very beginning, suggesting that they are the most similar country pairs in terms of country-level transport policy support. The two countries are geographically far away from each other and have ultimately different climate. This finding suggests that even these two countries are far away, people in the two countries share similar visions in terms of transportation infrastructure and service provision. It might be beneficial if the two countries can learn from each other, discussing approaches from different perspectives but aiming at similar public pursuit.

Malaysia in the first red color block is also one interesting example. The clustering suggests that Malaysia is similar to many of the Nordic countries, Germany and Austria. Not only Malaysia is physically far away from its clustered neighbors, it is also a developing country. It would be interesting to investigate more about if Malaysia has national policies that cultivate the transportation "culture" similar to that of Germany, Norway, Netherland, etc. Thus, the clustering by country ranking scores on a global scale is informative for countries to understand where it stands at the moment and know how other countries perform. If one country, for example, Columbia, has Norway as its role model, it might be hard to model the policies that Norway takes right away. Rather, it is possible to learn Argentina's path (in the second green box), given Argentina is closer to Norway in the clustering trees. The tree structure allows countries to identify possible learning opportunities across similar and dissimilar clusters.

Third, if NGOs want to promote certain type of projects, it is insightful to see if they have past experience in countries that share similar condition, at least similar public support atmosphere. This information enables various comparison. For example, if an NGO considers biking programs in Bahrain but has little information on its context, it could be worthwhile to collect data about Kenya, Morocco and Algeria, because these countries share similar aggregated policy support on transportation. Knowing those countries' aggregated attitudes would help roughly picture the public welcome or resistance level from the target country. Even though each country differs, preliminary research and comparison drawn from counterparts would help researchers/analysts anticipate difficulties beforehand.

5.4 Take-away Messages

This chapter focused on 50 country binary variables and analyzed their estimates with respect to univariate (ranking), bivariate and clustering analysis. We found that country-level variances indeed exist after we tease out the effects of individual-level socio-demographics, travel behavior, location characteristics, and attitudes. However, this observed variance in policy support does not align with service provision level across countries. For example, the countries like Netherland with the best biking infrastructure do not necessarily witness high support for more bike infrastructure from the public. We also found that support for some policies at the national level correlates with national economic indicators; one clear example is GDP and providing more roads. In fact, the development status "developing" vs. "developed" indicates different pattern. In developing countries, we find that higher GDP is significantly correlated with less public support for providing more roads. The reason might be that road infrastructure is a basic need to the economic activities and wellbeing of life; road provision is thus more like "necessary good" in the policy choice set in countries with very low GDP per capita.

Our cluster analysis provides three additional insights. First, countries that are geographically adjacent share similar country-level support across the 11 policies. This finding is reasonable as neighboring countries probably have similar political atmosphere, climate condition, and close conversations that foster policy learning. But we also find pairs like Singapore and Canada and Malaysia and Denmark that are far away geographically, but are clustered together. This result shows that even geographically separated countries may share similar transportation strategy and public may share similar vision on transportation/city development. This creates the opportunity for collaboratively learning. Lastly, the result is useful to NGOs to understand countries' conditions before implementing programs. Information on peer countries can complement prior knowledge of the local culture or context, at least in terms of expecting popular support for certain policy direction from the public.

6 An Alternative Model

This chapter provides an alternative modeling approach to account for the "up-to-three" restriction imposed by the survey question. Rather than treating support for each policy independently as outlined in Chapter 3, here we use maximum utility to model the joint support of multiple policies. This chapter only presents exploratory applications of this method to the dataset, but readers who are interested in addressing "more than one" choice in utility maximization problems may find it helpful. Furthermore, this approach of maximum utility estimation with more-than-one choices has been applied by Viegas de Lima, et.al. (2018) in their day travel pattern study in the Greater Boston Area.

One can think of the modelling approach as multi-nominal logit and each unique policy combination is one alternative in the choice set. The number of unique combinations of up-to-3 policies out of 11 is 232 (people can choose 0, 1, 2, or 3 policy items in any combination). In fact, in the survey we observe all 232 unique choice combinations. That means all possible combinations are covered by respondents.

Each choice's utility function includes pattern-specific parameters, such as policy-specific constants, socio-demographics, and the number of policies chosen. Also, the formulation includes policy-interaction parameters, capturing the added utility of having two or more policies chosen together. For example, I include variables capturing the joint selection of policy A "building additional roads" and J "providing more parking." I also include interactions of income with each policy, of gender with each policy, of being a bicyclist with each policy, etc. The interpretation of the parameters estimated, for example, biker * combinations that have policy A included, is thus the support of any alternative that has policy A included and if the individual is a biker. The interpretation is thus very similar to stating a biker tends to support policy A, or not.

Moreover, I am interested in getting more concrete implications, especially groups' preferences in specific countries/regions. Therefore, in this section, I added country interaction with socio-demographic variables in the modeling. In this way, we get estimates for the general socio-demographic groups as well as the socio-demographic groups in different countries. Those country-specific variables (e.g., income * US * policy A) together with general variables (like income worldwide) help us examine how public policy support held by different individuals may vary by country; this information can help researchers refine the scope of policy implication of this thesis.

Due to the large dataset and the large number of parameters to estimate in SEM, I subset the data to only include 5 countries and used sequential estimation rather than simultaneous estimation. The sequential scores of car pride are estimated by Multilevel CFA (Moody, 2019).

Fundamentally, simultaneous estimation is more efficient for estimating parameters but the large number of paths take significantly long time to run. Based on the country ranking, I selected 5 countries, Argentina, China, Denmark, United Arab Emirates and United States, that are of my research interests. The five countries are geographically separated and of unique characteristics: Denmark is one of the Nordic countries where green modes of transport are popular; the U.S. has the spirit of freedom in wide car use; China is of communism ideology with largest population; the United Arab Emirates is a high-income developing countries and Argentina can be one representative of Latin American countries where we see policies like expanding bike lanes are in particular popular.

I then tested gender, income and high education groups in those 5 countries to interact with policy support choices.

6.1 Model Results

The full table of result is attached in the Appendix. For country-specific variables, I fixed the parameters of Argentina as the reference; for other parameters, I always fixed those of policy B: discourage car use in center city as the reference.

High education groups in different countries exhibit distinct pattern, shown in Table 6.1. It seems that high education individuals tend to support policy H: Prioritize public bus lanes and/or bus rapid transit on average (this finding aligns with the finding in chapter 4). However, high education people tend not to prioritize this policy in the United Arab Emirates, Denmark, or the US compared to the same population group in Argentina or China, which is even higher than the reference country.

Additionally, it seems that high education individuals tend to support policy I: Provide clean energy-based public transportation options, since the parameter for variable "High Edu of clean transit" is 0.728 and significant. But it is not the case in all countries being selected. Again, the comparison is based on the baseline country—Argentina. So, the interpretation is that compared to Argentina, high education groups in all the other four countries are less likely to choose any combination that has I: clean energy transit in.

Table 6.1 Coefficients of high-education groups interacting with countries

Variable	Coefficient
High Edu in general	
High Edu of BRT prioritization	0.422*
High Edu of clean transit	0.728***
High Edu & BRT & country	

High Edu * BRT * AE	-0.121
High Edu * BRT * CN	0.560 **
High Edu * BRT * DK	-0.107
High Edu * BRT * US	-0.673 **
High Edu & clean transit & country	
High Edu * clean transit * AE	-1.15 ***
High Edu * clean transit * CN	-0.404 **
High Edu * clean transit * DK	-0.609 ***
High Edu * clean transit * US	-0.579 ***

Notes: regression coefficients by Biogeme;
p-value of two-tailed t-test against b = 0: * < 0.1, ** < .05, *** < .01

The effect of income on support for policy D: Expand public transportation services (bus/train) also varies across countries, shown in Table 6.2. Income among the five countries here negatively correlates to the support of more public transit, which is opposite to the finding in Chapter 4. Perhaps the difference is due to the different sample sizes. Higher income people in the United Arab Emirates are less likely to support public transit expansion compared to Argentina, but high-income individuals in China, Denmark and the US are more likely to do so. Note that the income variable has not been log-transformed as treated in the previous model so its magnitude is small.

Table 6.2 Coefficients of income interacting with countries.

Variable	Coefficient
Income in general	
Income * more PT	-1.23e-06
Income & more PT & country	
Income * more PT * AE	-1.46e-05
Income * more PT * CN	7.30e-05 **
Income * more PT * DK	2.99e-05
Income * more PT * US	4.87e-05

To summarize, this chapter briefly introduced another method to deal with the "up-to-three" choice limit in the survey question and presented initial exploration of interactions between certain socio-demographic groups and a few countries. The results imply that different socio-groups have different patterns of policy support across countries, suggesting there may be wide distributions around the global means estimated in Chapter 4.

7 Conclusion

7.1 Summary

Policy making is always evolving to respond and address societal problems. With many potential policies available to support sustainable transportation, it is important to consider which approach(es) are supported by whom and to what extent. By doing this we are able to anticipate potential implementation difficulties due to lack of public support and to segment population groups to make policies more actionable and targeted.

This thesis features breadth of respondents' geography and policy items. Traditionally the policy support literature in transportation focuses on pricing and congestion charging policies, but this research looks at 11 different transportation policies including pro-cars, pro-transit, pro-bike and walking, and clean energy vehicles. Furthermore, we look at support across these 11 policies in an international sample of 41,932 individuals in 51 countries/regions.

The results show that both individual- and country-level factors contribute to variances in policy support. From the individual-level analysis, we find that socio-demographics (like age and car ownership), travel mode, location characteristics, and attitudes all affect individual's policy support. Speaking of age, older individuals express lower support for building more roads and greater support for more and cheaper public transit and car-light CBD. They also express lower support for building pedestrian facilities, perhaps suggesting that these policies should address opportunities that enhance physical movement capability (probably older people are not able to walk much).

Owning cars compared to having access to cars indicates less support of policies, including improving transit services, pedestrian services, and car free city center. This may suggest that car ownership affects policy support differently than car access, where the former can result in stronger support for policies reinforcing automobile use and have less support for policies that improve other sustainable transportation means.

Nudges, education and advocacy on particular groups are possible given what they understand and support. For example, if people do not own cars but still have access to cars, their mobility needs can still be met but they may have less strong and exclusive opinions on car-oriented policies and may be more open to try out other alternatives. If government, TNC companies, NGOs or other advocates can promote programs like shared vehicles for the general public, the mindset of owning cars may be nudged and may result in higher share of alternative commuting modes. Similarly, for people who already own cars, they can be targeted with information of high-quality alternatives that may discourage his/her purchase of a second/third automobile.

Speaking of travel mode, it is clear that people generally support policies that are in their self-interest, but there are also some surprising results. All the modes share somewhat favorable attitude toward public transportation, except bike. Bicyclists have significantly negative support on roads, parking, transit expansion and lowering transit fares. But bikers support expanding bike lanes, discouraging car use in center city, and introducing car-free pedestrian zones in the city center. It seems that bikers have strong competing nature with cars and transit in this sense.

To extend this competing tension among car users, bikers and transit riders, transit riders tend not to prioritize road related policies or bike lane expansion policy as well. Meanwhile, transit riders would support all public transportation-related policies, including expanding public transportation services, prioritizing bus lane/BRT, lowering transit fares and providing clean energy-based public transportation options. It is interesting to notice the tension and competition of resources among these three modes; agencies may anticipate the support and opposition coming from different commuting groups if certain policies targeting on road/transit/bike is going to be announced.

Lastly, pedestrians tend to be supportive of most of the policies except building additional roads. Pedestrians' supportive attitudes on expanding bike lane and expanding transit service polices imply that walking is complementary to many other modes and that people do not have exclusive preferences for walking over other alternatives.

At the country level, we find that country-level variances exist even after we tease out the effects of individual-level socio-demographics, travel behavior, location characteristics, and attitudes. However, it is difficult to explain this observed variance in policy support across countries. For example, the countries with the best biking infrastructure do not necessarily witness high support for more bike infrastructure. However, we do find that support for some policies at the national level correlates with national economic indicators; one clear example is GDP and providing more roads. In fact, the development status "developing" vs. "developed" indicates different pattern. In developing countries, we find that higher GDP is significantly correlated with less public support for providing more roads. The reason might be that road infrastructure is a basic need to the economic activities and wellbeing of life; road provision is thus more like "necessary good" in the policy choice set in countries with very low GDP per capita.

Our cluster analysis provides three additional insights. First, countries that are geographically adjacent share similar country-level support across the 11 policies. This finding is reasonable as neighboring countries probably have similar political atmosphere, climate condition, and close conversations that foster policy learning. But we also find pairs like Singapore and Canada and Malaysia and Denmark that are far away geographically, but are clustered together. This result shows that even geographically separated countries may share similar transportation strategy and public may share similar vision on transportation/city development. This creates the opportunity for collaboratively learning. Lastly, the result is useful to NGOs to understand countries' conditions before implementing programs. Information on peer countries can complement prior knowledge of the local culture or context, at least in terms of expecting popular support for certain policy direction from the public.

However, despite correlation with some country-level factors, the country-level variances lack more powerful explanation as to their justifications. This may require future work of collecting larger sample size and variables pertaining to countries' culture and ideology (which are in general hard to quantify). More will be discussed in the limitation and future work.

7.2 Limitation and Future Work

This research takes a general approach to understand the average support for 11 transportation policies at a global scale. The results cannot be used to directly inform policy making at localities without first accounting for local context. This limitation can be further addressed by allowing variables to interact with countries like what we did in chapter 6 or building a random effect (or multilevel) model to allowing slopes of variables to change by countries. Therefore, for example, income will have different slopes estimated with respect to data of each country; we shall know who income varies across 51 countries/regions. Admittedly, this much more complex model may require greater computation power to solve convergence problems. But further down the stream, resolution higher than country-level is not feasible, as the survey design did not impose quota on the city level to have respondents' profile mimic the true city population's socio-demographics. I admit that policies are often being made at the city, county or other small unit; but this study provides a global overview that informs the overall trend, other than offers precise guideline for specific places.

Regarding the country-level analysis in Chapter 5, we could extend our categorization of countries to look at indicators other than GDP. For example, we could also to categorize countries to high and low urban density countries. The implication may target on different types of countries and predict the trends accordingly. For example, for countries stepping into higher urbanization rate, the results can suggest what transportation policies that their publics prioritize.

To really understand the differences among countries in terms of policy support, we think more close examination on historical practice, national policies, and master plans can be helpful. We believe that political environment, service provision, and culture can influence people's mindset and therefore policy support. For example, Malaysia is similar to Denmark and Germany in country-level policy support; this may not be explained by quantitative method but perhaps a qualitative research on national evolvement and advancement on transportation can be useful.

Another note is on the more-than-single-choice problem. Chapter 6 briefly presents one way to address this constraint in the survey question, but the computation power increases a lot. In future studies, framing/wording of the survey question could allow people to support other policies as well, even though they do not choose them as their top three choices. The framing of the research question then requires extra care on illustrating the “real” support and policy prioritization. Another approach to design the survey is to ask people to rank their choices. Then by the utility theory, people always take the alternative that maximizes his/her utility first; by ranking sequence, we can model which option gives the person the highest utility and which gives the second highest (it becomes the highest after we take the ranking #1 item out of the choices set).

7.3 Final Words

Sustainable transportation is critical for our global sustainability goals, but identifying effective and equitable policies can be a difficult task. We hope this study is able to offer insights for decision makers to better understand and therefore respond to the public view, and finally plan for a sustainable transportation future collaboratively with the public.

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9 Appendices

9.1 Mplus Code for Modelling in Chapter 4 & 5

I attach the model framework in Mplus for policy A: Building More road.

```
TITLE:          MPlus_Dalia_policy_support_questionA
 DATA:
         FILE IS /Users/xuenanni/Desktop/thesis/Mplus/pol_supp.txt;

  VARIABLE:
         NAMES ARE

         ind_ID country_ID
       q04A  q04B  q04C  q04D  q04E  q04F  q04G  q04H  q04I  q04J  q04K
       age gen  inc
       q01D q01E q01A q01K q01O q02 q09 q10 ess
       q14A q14B q14C  q14D  q14E  q14F  q14G  q14H  q14I  q14J  q14K  q14L  q14X
       q15A q15B q15C q15D q15E q15F popden
       low_edu high_edu
       access owning rail other peer tt_week miles_day
       AE  AR AT AU BE BH BR CA CH CL CN CO DE DK DZ EC EG ES FR GB GR HK ID
       IE IL IN IT JP KE KR MA MX MY NL NO PE PH PK PL PT RU SA SE SG TH TR UA
       US VE VN  ZA;


   USEVARIABLES ARE

          ind_ID   country_ID
        q04A
        age  gen  inc
        q14A q14B q14F q14K q15A q15B q15C q15D q15F
        ess   low_edu  high_edu  popden
        access  owning
        q01D q01E q01A  q01K q01O  rail
        AE  AR AT AU BE BH BR CA CH CL CN CO DE DK DZ EC EG ES FR GB GR HK
ID
        IE IL IN IT JP KE KR MA MX MY NL NO PE PH PK PL PT RU SA SE SG TH TR UA
        US VE VN;


   CATEGORICAL = q04A q14A q14B q14F q14K q15A q15B q15C q15D q15F;

   CLUSTER = country_ID; !leave the cluster = xx for typle = complex ! single level model
   IDVARIABLE = ind_ID;
   MISSING = ALL (-9999);
```

```
ANALYSIS:
   TYPE = COMPLEX;
   ESTIMATOR = MLR;
   INTEGRATION = MONTECARLO;


MODEL: !No within and between;
    !Latent variable measurement model for carpride
    carpride BY q14A* q14B q14F q14K q15A q15B q15C q15D q15F;
    carpride @ 1;

    !Regression of car pride on socio-demographics
    !carpride ON age gender income;

    !choice model
    q04A ON age  gen  low_edu  high_edu  inc
          ess access  owning carpride popden
          q01D q01E q01A  q01K q01O  rail
          AE  AR AT AU BE BH BR CA CH CL CN CO DE DK DZ EC EG ES FR GB GR HK
ID
          IE IL IN IT JP KE KR MA MX MY NL NO PE PH PK PL PT RU SA SE SG TH TR
UA
          US VE VN;
          inc;


OUTPUT:
   STD STDY STDYX;
SAVEDATA:

   RESULTS ARE /Users/xuenanni/Desktop/thesis/Mplus/resultA.dat
```

9.2 Biogeme Code for Modelling in Chapter 6

```
# Updated Dec. 17, 2018 by Xuenan

# from math import *
from biogeme import *
from headers import *
from loglikelihood import *
from statistics import *
from distributions import *

# BINARIES FOR TOUR NUMBER, PURPOSE, AND COMBINATION INPUTS
```

```
# binaries for number of tours in each option
OnePol =
[0,0,0,1,1,0,0,0,0,0,0,1,0,0,0,0,0,0,1,0,1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
1,0,0,0,0,0,0,0,0,0,
0,0,1,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]

TwoPol =
[1,1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,1,0,0,1,0,0,0,0,0,0,1,0,0,1,0,0,0,0,1,0,
0,0,0,0,0,0,1,0,1,0,1,0,0,0,1,1,1,0,0,0,0,0,1,1,1,0,0,1,1,1,0,0,0,0,0,1,1,1,0,0,0,1,0,1,0,0,0,0,1,0,0,
0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,
0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,0,0,0,0,1,0,0,1,0,0,0,0,0,0,1,0,1,0,0,0,1,1,0,1,0,0,0,1,0,0,1,0,0,0,1,1,0,
1,0,1,0,1,0,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,1,0,0]

ThreePol =
[0,0,1,0,0,1,1,0,1,1,1,0,1,0,1,1,1,1,0,1,0,1,1,0,1,1,0,0,1,0,1,0,1,1,0,0,1,1,1,1,1,0,1,1,0,1,1,1,1,0,1,
0,1,1,1,1,1,1,0,1,0,1,0,0,1,0,
0,0,0,1,1,1,0,1,0,0,0,1,1,0,0,0,1,1,1,1,1,0,0,0,1,1,1,0,1,0,1,1,1,1,0,1,1,1,1,1,1,1,1,1,0,1,1,1,1,1,1,1,
1,1,1,1,0,1,1,1,1,1,0,0,0,1,1,1,1,1,
1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,0,0,1,1,1,1,1,1,1,0,1,1,1,1,1,1,1,0,1,1,1,1,0,1,1,0,1,1,1,1,1,1,0,1,0,1,
1,1,0,0,1,0,1,1,1,0,1,1,0,1,1,1,
0,0,1,0,1,0,1,0,1,1,1,1,1,1,1,1,0,1,1,1,0,1,1,1,1,0,1,1]

ZeroPol =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
# binaries for existance of that specific purpose of tour

polA =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,1,0,1,0,0,0,1,0,0,1,0,0,1,0,1,0,0,1,0,0,0,0,1,0,0,0,0,0,0,1,0,1,0,0,0,
0,0,0,1,1,0,0,0,1,0,0,0,0,1,0,0,0,0,0,0,0,0,1,1,0,0,1,1,1,1,0,1,0,0,0,0,0,0,1,0,1,0,1,1,1,0,1,1,0,0,0,1,
1,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,1,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,0,1,0,0,0,1,0,1,0,1,0,0,0,
0,0,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,1,0,1,0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,1,0,0,1,0,1,0,0,1,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,1,0,0,1]
polB =
[0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,1,1,1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,1,0,0,1,1,0,0,0,1,1,0,0,1,0,1,
0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,1,0,0,0,1,0,0,1,0,0,0,1,1,0,0,0,0,0,
1,0,1,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,1,0,1,0,0,0,1,0,0,0,0,0,0,0,1,0,0,0,1,0,1,0,0,0,1,0,0,0,0,0,
0,0,0,0,0,0,1,0,1,0,1,0,1,0,0,0,0,0,0,0,1,0,0,1,0,0,1,0,0,1,0,0,1,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,1,1,0,0,
1,0,0,0,0,0,0,0,0,1,0,1,0,0,0,0,1,0,1,1,0,1,0,0,0]
```

polC =
[1,0,0,0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,1,1,0,1,0,0,0,0,0,0,0,
1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,1,
0,0,1,0,0,0,0,1,0,1,0,0,1,0,0,1,0,0,0,0,1,1,1,0,0,0,1,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,1,1,1,1,1,0,0,0,0,0,
1,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,1,0,1,0,0,1,1,1,0,0,0,1,0,1,0,0,0,0,1,0,0,1,0,1,0,1,1,0,0,0,1,
1,0,1,1,0,0,0,1,1,0,1,0,0,0,1,0,0,0,0,0,1,0,1,0,1]
polD =
[0,0,0,0,1,1,0,1,0,1,1,0,1,0,0,1,0,0,0,1,0,1,0,0,1,0,0,1,1,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,0,1,0,0,
0,1,0,0,1,0,1,1,0,0,1,1,0,1,0,0,0,0,0,1,1,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,
1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,1,1,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,1,1,0,0,0,0,0,1,0,1,0,1,0,1,1,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,1,0,0,1,0,
0,0,0,0,0,1,1,0,0,0,1,1,1,0,0,0,0,0,1,0,0,0,0,0,0]
polE =
[0,0,0,0,0,1,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,
0,0,1,1,1,0,0,0,0,0,0,0,0,0,1,1,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,1,0,0,0,0,0,0,1,1,0,1,0,0,1,1,1,0,1,0,0,1,0,0,0,1,0,0,0,0,0,1,0,1,1,1,1,0,1,1,0,0,0,0,0,0,0,1,1,1,
0,0,0,1,1,1,0,0,1,0,0,0,1,0,0,0,1,0,0,1,0,0,1,0,0,0,0,1,0,0,1,0,0,0,0,1,0,1,1,0,1,0,0,1,0,0,0,0,0,0,0,1,
0,1,0,1,0,0,0,0,1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0]
polF =
[0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,0,0,1,0,1,0,0,0,0,0,0,0,0,0,0,1,0,1,0,0,1,0,1,0,0,0,0,0,0,1,0,1,0,0,0,0,0,
0,0,0,0,0,1,0,0,1,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,1,0,0,0,1,1,0,0,0,0,0,0,1,0,0,0,0,0,0,1,1,
0,0,0,0,0,1,0,0,0,0,0,0,0,1,0,1,1,1,0,0,1,0,1,0,0,0,0,1,0,0,0,0,1,0,0,1,1,0,0,1,0,0,0,1,0,0,0,0,1,0,0,1,
0,0,0,1,0,1,0,1,0,0,0,0,1,1,0,0,0,0,1,0,1,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,1,0,0,0,1,0,0,1,0,0,0,
0,0,1,1,0,0,1,0,0,1,0,0,0,0,1,1,0,0,0,0,0,1,0,0,0]
polG =
[0,1,1,0,0,0,0,0,1,1,0,1,0,0,0,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,1,0,0,0,0,0,1,0,1,0,1,1,0,1,0,1,0,1,1,
0,1,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,1,1,0,1,0,0,1,1,0,0,0,0,0,0,0,1,0,0,1,0,1,1,0,1,0,0,0,0,0,0,1,1,0,
0,1,0,1,0,1,1,0,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,1,0,0,0,1,0,0,0,0,0,1,1,0,0,0,0,0,0,0,1,0,0,1,0,
1,1,0,0,0,0,0,0,0,0,1,0,0,1,0,1,1,0,0,0,0,0,0,0,0,1,0,0,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,1,1,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
polH =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,1,0,
0,0,0,0,0,1,1,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,1,0,1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,1,0,0,0,0,1,0,
0,0,0,1,1,0,0,0,1,0,1,1,0,0,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,1,0,1,1,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,1,0,1,1,1,0,0,0,1,1,1,1,0,0,0,0,0,1,0,0,0,0,1,1,0,1,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,1,0,
0,1,0,0,1,1,0,1,0,0,0,0,1,1,0,1,1,1,0,0,1,0,1,1,1]
polI =
[1,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,1,0,0,0,1,1,0,1,0,1,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,
0,0,0,0,0,0,0,1,0,0,0,0,1,1,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,1,0,0,1,0,0,0,
0,0,1,0,0,0,1,0,0,0,0,1,0,1,0,0,0,0,0,1,0,0,0,0,1,0,0,1,0,1,1,0,0,1,0,0,0,1,1,0,0,0,0,0,0,0,0,1,1,0,0,0,
0,1,1,0,1,1,1,0,0,0,0,0,0,0,0,1,0,0,0,0,1,1,0,0,1,1,0,1,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,1,1,0,0,1,0,0,0,0,0,
0,0,0,0,1,0,1,1,0,0,0,0,0,0,1,1,0,0,0,1,0,0,0,1,0]
polJ =
[0,0,1,1,0,0,1,1,0,0,1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,1,1,0,1,0,0,1,0,0,0,0,1,0,0,1,0,0,1,0,0,0,1,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,1,1,0,1,0,0,1,0,1,0,1,0,0,1,0,1,1,1,0,0,0,0,1,0,1,0,1,0,0,0,0,1,0,0,0,
0,0,0,0,1,1,1,1,1,1,1,0,0,1,0,1,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,1,

```
1,0,1,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,
0,0,0,0,0,1,0,0,0,1,0,1,0,0,0,0,0,1,0,0,0,0,0,1,0]
polK =
[0,1,1,0,0,0,1,0,0,0,0,0,1,1,0,0,0,1,0,0,0,0,0,0,0,1,0,0,0,1,0,0,1,0,1,0,0,0,0,1,0,0,0,0,0,0,0,0,1,0,1,
0,1,0,1,0,0,0,0,0,1,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,
0,1,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,1,0,0,1,0,0,0,0,1,1,0,0,0,1,0,1,0,0,0,0,1,1,0,0,0,1,0,0,0,1,0,0,
0,1,1,1,0,0,0,0,0,1,0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,0,1,0,0,0,0,0,0,0,0,1,0,1,1,0,1,0,0,0,0,0,
0,1,0,0,0,0,0,0,1,0,1,0,1,1,0,0,1,0,0,0,1,0,0,0,0]

# binary for tour purpose combination
A_J =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
D_H =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,1,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,
0,0,0,0,0,0,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
B_F =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,
0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0]
C_E =
[0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,
0,0,0,1,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
A_F =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,1,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0]
I_K =
[0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
```

```
H_B =
[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,1,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0]


# creation of binary variables above for each of the 232 alternatives
counter = 0
for i in range(1,233):
	counter = counter + 1
	exec("onepolicy%s = OnePol[i-1]" % (counter))
	exec("twopolicy%s = TwoPol[i-1]" % (counter))
	exec("threepolicy%s = ThreePol[i-1]" % (counter))
	exec("zeropolicy%s = ZeroPol[i-1]" % (counter))
	exec("A%s = polA[i-1]" % (counter))
	exec("B%s = polB[i-1]" % (counter))
	exec("C%s = polC[i-1]" % (counter))
	exec("D%s = polD[i-1]" % (counter))
	exec("E%s = polE[i-1]" % (counter))
	exec("F%s = polF[i-1]" % (counter))
	exec("G%s = polG[i-1]" % (counter))
	exec("H%s = polH[i-1]" % (counter))
	exec("I%s = polI[i-1]" % (counter))
	exec("J%s = polJ[i-1]" % (counter))
	exec("K%s = polK[i-1]" % (counter))
	exec("AJ%s = A_J[i-1]" % (counter))
	exec("DH%s = D_H[i-1]" % (counter))
	exec("BF%s = B_F[i-1]" % (counter))
	exec("CE%s = C_E[i-1]" % (counter))
	exec("AF%s = A_F[i-1]" % (counter))
	exec("IK%s = I_K[i-1]" % (counter))
	exec("HB%s = H_B[i-1]" % (counter))

# PARAMETERS

# Tour constants
# purpose
beta_A = Beta('beta_A',0,-100,100,0)
beta_B = Beta('beta_B',0,-100,100,1)
beta_C = Beta('beta_C',0,-100,100,0)
beta_D = Beta('beta_D',0,-100,100,0)
beta_E = Beta('beta_E',0,-100,100,0)
beta_F = Beta('beta_F',0,-100,100,0)
beta_G = Beta('beta_G',0,-100,100,0)
```

```
beta_H = Beta('beta_H',0,-100,100,0)
beta_I = Beta('beta_I',0,-100,100,0)
beta_J = Beta('beta_J',0,-100,100,0)
beta_K = Beta('beta_K',0,-100,100,0)

# number of tours
beta_zeropolicy = Beta('beta_zeropolicy',0,-100,100,1)
beta_onepolicy = Beta('beta_onepolicy',0,-100,100,1)
beta_twopolicy = Beta('beta_twopolicy',0,-100,100,1)
beta_threepolicy = Beta('beta_threepolicy',0,-100,100,0)
#beta_fourtours = Beta('beta_fourtours',0,-100,100,1)

# combination of tour purposes
beta_AJ = Beta('beta_AJ',0,-10,10,0)
beta_DH = Beta('beta_DH',0,-10,10,0)
beta_BF = Beta('beta_BF',0,-10,10,1)
beta_CE = Beta('beta_CE',0,-10,10,0)
beta_AF = Beta('beta_AF',0,-10,10,0)
beta_IK = Beta('beta_IK',0,-10,10,0)
beta_HB = Beta('beta_HB',0,-10,10,0)
# Person type

# Adult gender
# male as a base
beta_female_A = Beta('beta_female_A',0,-10,10,0)
beta_female_B = Beta('beta_female_B',0,-10,10,1)
beta_female_C = Beta('beta_female_C',0,-10,10,0)
beta_female_D = Beta('beta_female_D',0,-10,10,0)
beta_female_E = Beta('beta_female_E',0,-10,10,0)
beta_female_F = Beta('beta_female_F',0,-10,10,0)
beta_female_G = Beta('beta_female_G',0,-10,10,0)
beta_female_H = Beta('beta_female_H',0,-10,10,0)
beta_female_I = Beta('beta_female_I',0,-10,10,0)
beta_female_J = Beta('beta_female_J',0,-10,10,0)
beta_female_K = Beta('beta_female_K',0,-10,10,0)
#C: bike
beta_female_C_AE = Beta('beta_female_C_AE',0,-10,10,0)
beta_female_C_AR = Beta('beta_female_C_AR',0,-10,10,1)
beta_female_C_US = Beta('beta_female_C_US',0,-10,10,0)
beta_female_C_DK = Beta('beta_female_C_DK',0,-10,10,0)
beta_female_C_CN = Beta('beta_female_C_CN',0,-10,10,0)

#D: expanding public transit
beta_female_D_AE = Beta('beta_female_D_AE',0,-10,10,0)
beta_female_D_AR = Beta('beta_female_D_AR',0,-10,10,1)
beta_female_D_US = Beta('beta_female_D_US',0,-10,10,0)
```

```
beta_female_D_DK = Beta('beta_female_D_DK',0,-10,10,0)
beta_female_D_CN = Beta('beta_female_D_CN',0,-10,10,0)

# E: pedestrain
beta_female_E_AE = Beta('beta_female_E_AE',0,-10,10,0)
beta_female_E_AR = Beta('beta_female_E_AR',0,-10,10,1)
beta_female_E_US = Beta('beta_female_E_US',0,-10,10,0)
beta_female_E_DK = Beta('beta_female_E_DK',0,-10,10,0)
beta_female_E_CN = Beta('beta_female_E_CN',0,-10,10,0)

#income  A, D, H, K
#A: more roads
beta_inc_A_AE = Beta('beta_inc_A_AE',0,-10,10,0)
beta_inc_A_AR = Beta('beta_inc_A_AR',0,-10,10,1)
beta_inc_A_US = Beta('beta_inc_A_US',0,-10,10,0)
beta_inc_A_DK = Beta('beta_inc_A_DK',0,-10,10,0)
beta_inc_A_CN = Beta('beta_inc_A_CN',0,-10,10,0)
#D: expanding public transit
beta_inc_D_AE = Beta('beta_inc_D_AE',0,-10,10,0)
beta_inc_D_AR = Beta('beta_inc_D_AR',0,-10,10,1)
beta_inc_D_US = Beta('beta_inc_D_US',0,-10,10,0)
beta_inc_D_DK = Beta('beta_inc_D_DK',0,-10,10,0)
beta_inc_D_CN = Beta('beta_inc_D_CN',0,-10,10,0)
#H: Prioritizing BRT
beta_inc_H_AE = Beta('beta_inc_H_AE',0,-10,10,0)
beta_inc_H_AR = Beta('beta_inc_H_AR',0,-10,10,1)
beta_inc_H_US = Beta('beta_inc_H_US',0,-10,10,0)
beta_inc_H_DK = Beta('beta_inc_H_DK',0,-10,10,0)
beta_inc_H_CN = Beta('beta_inc_H_CN',0,-10,10,0)

#K: Clean Energy Vehicle
beta_inc_K_AE = Beta('beta_inc_K_AE',0,-10,10,0)
beta_inc_K_AR = Beta('beta_inc_K_AR',0,-10,10,1)
beta_inc_K_US = Beta('beta_inc_K_US',0,-10,10,0)
beta_inc_K_DK = Beta('beta_inc_K_DK',0,-10,10,0)
beta_inc_K_CN = Beta('beta_inc_K_CN',0,-10,10,0)


#inc in general
BETA_inc_A = Beta('BETA_inc_A',0.0,-1000,1000,0)
BETA_inc_B = Beta('BETA_inc_B',0.0,-1000,1000,1)
BETA_inc_C = Beta('BETA_inc_C',0.0,-1000,1000,0)
BETA_inc_D = Beta('BETA_inc_D',0.0,-1000,1000,0)
BETA_inc_E = Beta('BETA_inc_E',0.0,-1000,1000,0)
BETA_inc_F = Beta('BETA_inc_F',0.0,-1000,1000,0)
BETA_inc_G = Beta('BETA_inc_G',0.0,-1000,1000,0)
```

```
BETA_inc_H = Beta('BETA_inc_H',0.0,-1000,1000,0)
BETA_inc_I = Beta('BETA_inc_I',0.0,-1000,1000,0)
BETA_inc_J = Beta('BETA_inc_J',0.0,-1000,1000,0)
BETA_inc_K = Beta('BETA_inc_K',0.0,-1000,1000,0)

#high_edu
BETA_hi_A = Beta('BETA_hi_A',0.0,-1000,1000,0)
BETA_hi_B = Beta('BETA_hi_B',0.0,-1000,1000,1)
BETA_hi_C = Beta('BETA_hi_C',0.0,-1000,1000,0)
BETA_hi_D = Beta('BETA_hi_D',0.0,-1000,1000,0)
BETA_hi_E = Beta('BETA_hi_E',0.0,-1000,1000,0)
BETA_hi_F = Beta('BETA_hi_F',0.0,-1000,1000,0)
BETA_hi_G = Beta('BETA_hi_G',0.0,-1000,1000,0)
BETA_hi_H = Beta('BETA_hi_H',0.0,-1000,1000,0)
BETA_hi_I = Beta('BETA_hi_I',0.0,-1000,1000,0)
BETA_hi_J = Beta('BETA_hi_J',0.0,-1000,1000,0)
BETA_hi_K = Beta('BETA_hi_K',0.0,-1000,1000,0)

#DL expand transit
beta_he_D_AE = Beta('beta_he_D_AE',0,-10,10,0)
beta_he_D_AR = Beta('beta_he_D_AR',0,-10,10,1)
beta_he_D_US = Beta('beta_he_D_US',0,-10,10,0)
beta_he_D_DK = Beta('beta_he_D_DK',0,-10,10,0)
beta_he_D_CN = Beta('beta_he_D_CN',0,-10,10,0)

#H: prio transit
beta_he_H_AE = Beta('beta_he_H_AE',0,-10,10,0)
beta_he_H_AR = Beta('beta_he_H_AR',0,-10,10,1)
beta_he_H_US = Beta('beta_he_H_US',0,-10,10,0)
beta_he_H_DK = Beta('beta_he_H_DK',0,-10,10,0)
beta_he_H_CN = Beta('beta_he_H_CN',0,-10,10,0)

#clean energy transit
beta_he_I_AE = Beta('beta_he_I_AE',0,-10,10,0)
beta_he_I_AR = Beta('beta_he_I_AR',0,-10,10,1)
beta_he_I_US = Beta('beta_he_I_US',0,-10,10,0)
beta_he_I_DK = Beta('beta_he_I_DK',0,-10,10,0)
beta_he_I_CN = Beta('beta_he_I_CN',0,-10,10,0)

#mode--driver
BETA_driver_A = Beta('BETA_driver_A',0.0,-1000,1000,0)
BETA_driver_B = Beta('BETA_driver_B',0.0,-1000,1000,1)
BETA_driver_C = Beta('BETA_driver_C',0.0,-1000,1000,0)
BETA_driver_D = Beta('BETA_driver_D',0.0,-1000,1000,0)
BETA_driver_E = Beta('BETA_driver_E',0.0,-1000,1000,0)
BETA_driver_F = Beta('BETA_driver_F',0.0,-1000,1000,0)
```

```
BETA_driver_G = Beta('BETA_driver_G',0.0,-1000,1000,0)
BETA_driver_H = Beta('BETA_driver_H',0.0,-1000,1000,0)
BETA_driver_I = Beta('BETA_driver_I',0.0,-1000,1000,0)
BETA_driver_J = Beta('BETA_driver_J',0.0,-1000,1000,0)
BETA_driver_K = Beta('BETA_driver_K',0.0,-1000,1000,0)
#D: expand transit
beta_drive_D_AE = Beta('beta_drive_D_AE',0,-10,10,0)
beta_drive_D_AR = Beta('beta_drive_D_AR',0,-10,10,1)
beta_drive_D_US = Beta('beta_drive_D_US',0,-10,10,0)
beta_drive_D_DK = Beta('beta_drive_D_DK',0,-10,10,0)
beta_drive_D_CN = Beta('beta_drive_D_CN',0,-10,10,0)
#mode--transit
BETA_transit_A = Beta('BETA_transit_A',0.0,-1000,1000,0)
BETA_transit_B = Beta('BETA_transit_B',0.0,-1000,1000,1)
BETA_transit_C = Beta('BETA_transit_C',0.0,-1000,1000,0)
BETA_transit_D = Beta('BETA_transit_D',0.0,-1000,1000,0)
BETA_transit_E = Beta('BETA_transit_E',0.0,-1000,1000,0)
BETA_transit_F = Beta('BETA_transit_F',0.0,-1000,1000,0)
BETA_transit_G = Beta('BETA_transit_G',0.0,-1000,1000,0)
BETA_transit_H = Beta('BETA_transit_H',0.0,-1000,1000,0)
BETA_transit_I = Beta('BETA_transit_I',0.0,-1000,1000,0)
BETA_transit_J = Beta('BETA_transit_J',0.0,-1000,1000,0)
BETA_transit_K = Beta('BETA_transit_K',0.0,-1000,1000,0)
#C:bike
beta_tran_C_AE = Beta('beta_tran_C_AE',0,-10,10,0)
beta_tran_C_AR = Beta('beta_tran_C_AR',0,-10,10,1)
beta_tran_C_US = Beta('beta_tran_C_US',0,-10,10,0)
beta_tran_C_DK = Beta('beta_tran_C_DK',0,-10,10,0)
beta_tran_C_CN = Beta('beta_tran_C_CN',0,-10,10,0)

#mode-bike
BETA_bike_A = Beta('BETA_bike_A',0.0,-1000,1000,0)
BETA_bike_B = Beta('BETA_bike_B',0.0,-1000,1000,1)
BETA_bike_C = Beta('BETA_bike_C',0.0,-1000,1000,0)
BETA_bike_D = Beta('BETA_bike_D',0.0,-1000,1000,0)
BETA_bike_E = Beta('BETA_bike_E',0.0,-1000,1000,0)
BETA_bike_F = Beta('BETA_bike_F',0.0,-1000,1000,0)
BETA_bike_G = Beta('BETA_bike_G',0.0,-1000,1000,0)
BETA_bike_H = Beta('BETA_bike_H',0.0,-1000,1000,0)
BETA_bike_I = Beta('BETA_bike_I',0.0,-1000,1000,0)
BETA_bike_J = Beta('BETA_bike_J',0.0,-1000,1000,0)
BETA_bike_K = Beta('BETA_bike_K',0.0,-1000,1000,0)

#ownining a car

BETA_own_A = Beta('BETA_own_A',0.0,-1000,1000,0)
```

```
BETA_own_B = Beta('BETA_own_B',0.0,-1000,1000,1)
BETA_own_C = Beta('BETA_own_C',0.0,-1000,1000,0)
BETA_own_D = Beta('BETA_own_D',0.0,-1000,1000,0)
BETA_own_E = Beta('BETA_own_E',0.0,-1000,1000,0)
BETA_own_F = Beta('BETA_own_F',0.0,-1000,1000,0)
BETA_own_G = Beta('BETA_own_G',0.0,-1000,1000,0)
BETA_own_H = Beta('BETA_own_H',0.0,-1000,1000,0)
BETA_own_I = Beta('BETA_own_I',0.0,-1000,1000,0)
BETA_own_J = Beta('BETA_own_J',0.0,-1000,1000,0)
BETA_own_K = Beta('BETA_own_K',0.0,-1000,1000,0)

### Latent variable: structural equation

# Note that the expression must be on a single line. In order to
# write it across several lines, each line must terminate with
# the \ symbol

# car pride
beta_cp_B = Beta('beta_cp_B',-1,-10,10,1)
beta_cp_A = Beta('beta_cp_A',0,-10,10,0)
beta_cp_C = Beta('beta_cp_A',0,-10,10,0)
beta_cp_D = Beta('beta_cp_D',0,-10,10,0)
beta_cp_E = Beta('beta_cp_E',0,-10,10,0)
beta_cp_F = Beta('beta_cp_F',0,-10,10,0)
beta_cp_G = Beta('beta_cp_G',0,-10,10,0)
beta_cp_H = Beta('beta_cp_H',0,-10,10,0)
beta_cp_I = Beta('beta_cp_I',0,-10,10,0)
beta_cp_J = Beta('beta_cp_J',0,-10,10,0)
beta_cp_K = Beta('beta_cp_K',0,-10,10,0)

# Choice set
counter = 0
choiceset = range(1,233)

# Utility equations
for i in range(1,233):
        counter = counter + 1
        print(i)
        exec("V_%s = beta_A * (A%s) +  beta_B * (B%s)  + beta_C * (C%s)  + beta_D * (D%s)
+ beta_E * (E%s)  +beta_F * (F%s) + beta_G * (G%s) + beta_H * (H%s) + beta_I * (I%s) +
beta_J * (J%s)+ beta_K * (K%s) +\
                beta_AJ * (AJ%s) + beta_DH * (DH%s) + beta_BF * (BF%s) + beta_CE
*(CE%s) + beta_AF*(AF%s)+beta_IK*(IK%s)+ beta_HB*(HB%s)+\
beta_female_A * (A%s * gen) + beta_female_B * (B%s * gen) + beta_female_C * (C%s * gen)
+\
```

```
    beta_female_D * (D%s * gen) + beta_female_E * (E%s * gen) + beta_female_F * (F%s * 
gen)  +\
    beta_female_G * (G%s * gen) + beta_female_H * (H%s * gen) + beta_female_I * (I%s * gen) 
+\
    beta_female_J * (J%s * gen) + beta_female_K * (K%s * gen) +\
    beta_female_D_AE * (D%s * gen * AE) + beta_female_D_AR * (D%s * gen * AR) + 
beta_female_D_US * (D%s * gen * US)  +\
    beta_female_D_DK * (D%s * gen * DK) + beta_female_D_CN * (D%s * gen * CN) +\
    beta_female_C_AE * (C%s * gen * AE) + beta_female_C_AR * (C%s * gen * AR) + 
beta_female_C_US * (C%s * gen * US)+\
    beta_female_C_DK * (C%s * gen * DK) + beta_female_C_CN * (C%s * gen * CN) +\
    beta_female_E_AE * (E%s * gen * AE) + beta_female_E_AR * (E%s * gen * AR) + 
beta_female_E_US * (E%s * gen * US)+\
    beta_female_E_DK * (E%s * gen * DK) + beta_female_E_CN * (E%s * gen * CN) +\
          BETA_hi_A * (A%s * high_edu)+ BETA_hi_B * (B%s * high_edu)+  BETA_hi_C * 
(C%s * high_edu)+    \
    BETA_hi_D * (D%s * high_edu)+ BETA_hi_E * (E%s * high_edu)+  BETA_hi_F * (F%s * 
high_edu)+    \
    BETA_hi_G * (G%s * high_edu)+ BETA_hi_H * (H%s * high_edu)+  BETA_hi_I * (I%s * 
high_edu)+    \
    BETA_hi_J * (J%s * high_edu)+ BETA_hi_K * (K%s * high_edu)+ \
          BETA_inc_A * (A%s * inc) + BETA_inc_B * (B%s * inc) + BETA_inc_C * (C%s * 
inc) +\
    BETA_inc_D * (D%s * inc) + BETA_inc_E * (E%s * inc) + BETA_inc_F * (F%s * inc) +\
    BETA_inc_G * (G%s * inc) + BETA_inc_H * (H%s * inc) + BETA_inc_I * (I%s * inc) +\
    BETA_inc_J * (J%s * inc) + BETA_inc_K * (K%s * inc)  +\
    beta_inc_A_AE * (A%s * inc * AE) + beta_inc_A_AR * (A%s * inc * AR) + beta_inc_A_US 
* (A%s * inc * US)+\
    beta_inc_A_DK * (A%s * inc * DK) +  beta_inc_A_CN * (A%s * inc * CN)  +\
    beta_inc_D_AE * (D%s * inc * AE) + beta_inc_D_AR * (D%s * inc * AR) + beta_inc_D_US 
* (D%s * inc * US)+\
    beta_inc_D_DK * (D%s * inc * DK) +  beta_inc_D_CN * (D%s * inc * CN)  +\
    beta_inc_H_AE * (H%s * inc * AE) +      beta_inc_H_AR * (H%s * inc * AR) + 
beta_inc_H_US * (H%s * inc * US)  +\
    beta_inc_H_DK * (H%s * inc * DK) +  beta_inc_H_CN * (H%s * inc * CN)  +\
    beta_inc_K_AE * (K%s * inc * AE) +      beta_inc_K_AR * (K%s * inc * AR) + 
beta_inc_K_US * (K%s * inc * US)  +\
    beta_inc_K_DK * (K%s * inc * DK) +  beta_inc_K_CN * (K%s * inc * CN)  +\
    beta_he_D_AE * (D%s * high_edu * AE) + beta_he_D_AR * (D%s * high_edu * AR) + 
beta_he_D_US * (D%s * high_edu* US)+\
    beta_he_D_DK * (D%s * high_edu * DK) +  beta_he_D_CN * (D%s * high_edu * CN)  +\
    beta_he_H_AE * (H%s * high_edu * AE) + beta_he_H_AR * (H%s * high_edu * AR) + 
beta_he_H_US * (H%s * high_edu* US)+\
    beta_he_H_DK * (H%s * high_edu * DK) +  beta_he_H_CN * (H%s * high_edu * CN)  +\
    beta_he_I_AE * (I%s * high_edu * AE) + beta_he_I_AR * (I%s * high_edu * AR) + 
beta_he_I_US * (I%s * high_edu* US)+\
```

```
   beta_he_I_DK * (I%s * high_edu * DK) +  beta_he_I_CN * (I%s * high_edu * CN)  +\
         BETA_driver_A * (A%s * q01D) + BETA_driver_B * (B%s * q01D) + BETA_driver_C
* (C%s * q01D)+\
   BETA_driver_D * (D%s * q01D) + BETA_driver_E * (E%s * q01D) + BETA_driver_F *
(F%s * q01D)+\
   BETA_driver_G * (G%s * q01D) + BETA_driver_H * (H%s * q01D) + BETA_driver_I *
(I%s * q01D)+\
   BETA_driver_J * (J%s * q01D) + BETA_driver_K * (K%s * q01D) +\
   beta_drive_D_AE * (D%s * q01D * AE) + beta_drive_D_AR * (D%s * q01D * AR) +
beta_drive_D_US * (D%s * q01D * US) +\
   beta_drive_D_DK * (D%s * q01D * DK) + beta_drive_D_CN * (D%s * q01D * CN)  +\
         BETA_transit_A * (A%s * rail) + BETA_transit_B * (B%s * rail) + BETA_transit_C *
(C%s * rail)+\
   BETA_transit_D * (D%s * rail) + BETA_transit_E * (E%s * rail) + BETA_transit_F * (F%s *
rail)+\
   BETA_transit_G * (G%s * rail) + BETA_transit_H * (H%s * rail) + BETA_transit_I * (I%s *
rail)+\
   BETA_transit_J * (J%s * rail) + BETA_transit_K * (K%s * rail) +\
         beta_tran_C_AE *(C%s * rail * AE) + beta_tran_C_AR * (C%s * rail * AR) +
beta_tran_C_US * (C%s * rail * US)+\
   beta_tran_C_DK * (C%s * rail * DK) + beta_tran_C_CN * (C%s * rail * CN) +\
         BETA_bike_A * (A%s * q01A) + BETA_bike_B * (B%s * q01A) + BETA_bike_C *
(C%s * q01A) +\
   BETA_bike_D * (D%s * q01A) + BETA_bike_E * (E%s * q01A) + BETA_bike_F * (F%s *
q01A) +\
   BETA_bike_G * (G%s * q01A) + BETA_bike_H * (H%s * q01A) + BETA_bike_I * (I%s *
q01A) +\
   BETA_bike_J * (J%s * q01A) + BETA_bike_K * (K%s * q01A) +\
   BETA_own_A * (A%s * owning) + BETA_own_B * (B%s * owning) + BETA_own_C *
(C%s * owning) +\
   BETA_own_D * (D%s * owning) + BETA_own_E * (E%s * owning) + BETA_own_F *
(F%s * owning) +\
   BETA_own_G * (G%s * owning) + BETA_own_H * (H%s * owning) + BETA_own_I *
(I%s * owning) +\
   BETA_own_J * (J%s * owning) + BETA_own_K * (K%s * owning) +\
   beta_cp_A * (A%s * cp) + beta_cp_B * (B%s * cp) + beta_cp_C * (C%s * cp) +\
   beta_cp_D * (D%s * cp) + beta_cp_E * (E%s * cp) + beta_cp_F * (F%s * cp)  +\
   beta_cp_G * (G%s * cp) + beta_cp_H * (H%s * cp) + beta_cp_I * (I%s * cp)  +\
   beta_cp_J * (J%s * cp) + beta_cp_K * (K%s * cp) +\
         beta_zeropolicy * (zeropolicy%s) + beta_onepolicy * (onepolicy%s) + beta_twopolicy *
(twopolicy%s) + \
         beta_threepolicy * (threepolicy%s)" % ((counter,)*171))   # 171  is the number of
parameters

V = dict(zip(range(1,233),[eval('V_%s' %i) for i in choiceset]))  # make V
av = dict(zip(range(1,233),[1]*232)) # now assume all are available
```

```
prob = bioLogit(V,av,choice)


rowIterator('obsIter')
BIOGEME_OBJECT.ESTIMATE = Sum(log(prob),'obsIter')
#exclude = (inc) < 0
#BIOGEME_OBJECT.EXCLUDE = exclude
#BIOGEME_OBJECT.ESTIMATE = Sum(loglike,'obsIter')
BIOGEME_OBJECT.PARAMETERS['numberOfThreads'] = '12'
BIOGEME_OBJECT.PARAMETERS['optimizationAlgorithm'] = 'CFSQP'
BIOGEME_OBJECT.PARAMETERS['checkDerivatives'] = '0'
BIOGEME_OBJECT.PARAMETERS['moreRobustToNumericalIssues'] = '1'
```

9.3 232 Alternatives: Sequential estimation results by Biogeme in Chapter 6

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
BETA_bike_A	0.315	0.136	2.31	0.02		0.135	2.33	0.02	
BETA_bike_C	1.33	0.119	11.15	0.00		0.129	10.36	0.00	
BETA_bike_D	0.186	0.117	1.59	0.11	*	0.124	1.50	0.13	*
BETA_bike_E	-0.0892	0.134	-0.67	0.50	*	0.139	-0.64	0.52	*
BETA_bike_F	0.552	0.142	3.89	0.00		0.150	3.69	0.00	
BETA_bike_G	0.605	0.102	5.93	0.00		0.114	5.32	0.00	
BETA_bike_H	0.303	0.136	2.23	0.03		0.139	2.17	0.03	
BETA_bike_I	0.296	0.119	2.48	0.01		0.122	2.42	0.02	
BETA_bike_J	0.102	0.120	0.85	0.40	*	0.126	0.81	0.42	*
BETA_bike_K	0.559	0.119	4.71	0.00		0.124	4.52	0.00	
BETA_driver_A	0.428	0.113	3.80	0.00		0.114	3.75	0.00	
BETA_driver_C	0.108	0.125	0.86	0.39	*	0.124	0.87	0.39	*
BETA_driver_D	0.335	0.224	1.50	0.13	*	0.233	1.44	0.15	*
BETA_driver_E	-0.135	0.109	-1.25	0.21	*	0.109	-1.24	0.21	*
BETA_driver_F	0.0365	0.136	0.27	0.79	*	0.143	0.26	0.80	*
BETA_driver_G	0.294	0.0918	3.20	0.00		0.0974	3.01	0.00	
BETA_driver_H	-0.139	0.126	-1.11	0.27	*	0.125	-1.12	0.26	*
BETA_driver_I	0.253	0.105	2.42	0.02		0.108	2.34	0.02	
BETA_driver_J	0.211	0.0962	2.19	0.03		0.101	2.10	0.04	
BETA_driver_K	0.414	0.105	3.96	0.00		0.109	3.80	0.00	
BETA_hi_A	0.394	0.0937	4.20	0.00		0.0930	4.23	0.00	

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
BETA_hi_C	0.260	0.103	2.53	0.01		0.107	2.42	0.02	
BETA_hi_D	0.932	0.199	4.68	0.00		0.205	4.55	0.00	
BETA_hi_E	0.303	0.0894	3.38	0.00		0.0909	3.33	0.00	
BETA_hi_F	0.147	0.111	1.33	0.18	*	0.114	1.29	0.20	*
BETA_hi_G	-0.0846	0.0748	-1.13	0.26	*	0.0811	-1.04	0.30	*
BETA_hi_H	0.422	0.244	1.73	0.08	*	0.234	1.81	0.07	*
BETA_hi_I	0.728	0.183	3.97	0.00		0.187	3.88	0.00	
BETA_hi_J	0.297	0.0801	3.70	0.00		0.0831	3.57	0.00	
BETA_hi_K	0.120	0.0862	1.39	0.16	*	0.0903	1.33	0.18	*
BETA_inc_A	5.62e-05	3.38e-05	1.66	0.10	*	3.39e-05	1.66	0.10	*
BETA_inc_C	7.76e-06	1.40e-05	0.55	0.58	*	1.47e-05	0.53	0.60	*
BETA_inc_D	-1.23e-06	2.15e-05	-0.06	0.95	*	2.21e-05	-0.06	0.96	*
BETA_inc_E	-1.17e-05	1.15e-05	-1.01	0.31	*	1.20e-05	-0.98	0.33	*
BETA_inc_F	3.30e-05	1.64e-05	2.01	0.04		1.70e-05	1.94	0.05	*
BETA_inc_G	2.81e-05	1.05e-05	2.68	0.01		1.12e-05	2.50	0.01	
BETA_inc_H	2.99e-05	2.99e-05	1.00	0.32	*	2.87e-05	1.04	0.30	*
BETA_inc_I	-1.18e-05	1.12e-05	-1.05	0.29	*	1.18e-05	-0.99	0.32	*
BETA_inc_J	6.04e-06	1.16e-05	0.52	0.60	*	1.21e-05	0.50	0.62	*
BETA_inc_K	5.33e-05	2.91e-05	1.83	0.07	*	2.96e-05	1.80	0.07	*
BETA_own_A	0.134	0.115	1.17	0.24	*	0.115	1.17	0.24	*
BETA_own_C	0.0877	0.121	0.72	0.47	*	0.121	0.73	0.47	*
BETA_own_D	0.101	0.0970	1.04	0.30	*	0.103	0.98	0.33	*
BETA_own_E	-0.0908	0.105	-0.86	0.39	*	0.105	-0.86	0.39	*
BETA_own_F	-0.0812	0.134	-0.61	0.54	*	0.140	-0.58	0.56	*
BETA_own_G	0.0252	0.0907	0.28	0.78	*	0.0965	0.26	0.79	*
BETA_own_H	-0.238	0.119	-1.99	0.05		0.121	-1.98	0.05	
BETA_own_I	-0.0218	0.102	-0.21	0.83	*	0.106	-0.21	0.84	*
BETA_own_J	0.511	0.0975	5.24	0.00		0.100	5.10	0.00	
BETA_own_K	0.379	0.105	3.59	0.00		0.110	3.46	0.00	
BETA_transit_A	0.139	0.135	1.03	0.30	*	0.136	1.03	0.30	*
BETA_transit_C	0.779	0.339	2.30	0.02		0.336	2.32	0.02	
BETA_transit_D	0.901	0.103	8.76	0.00		0.110	8.20	0.00	
BETA_transit_E	0.300	0.118	2.54	0.01		0.124	2.43	0.02	
BETA_transit_F	0.357	0.147	2.43	0.02		0.151	2.36	0.02	

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
BETA_transit_G	0.941	0.0976	9.64	0.00		0.107	8.80	0.00	
BETA_transit_H	0.708	0.118	6.01	0.00		0.122	5.80	0.00	
BETA_transit_I	0.596	0.109	5.45	0.00		0.117	5.11	0.00	
BETA_transit_J	0.375	0.112	3.36	0.00		0.115	3.25	0.00	
BETA_transit_K	0.686	0.113	6.08	0.00		0.117	5.86	0.00	
beta_A	-1.81	0.112	-16.09	0.00		0.112	-16.06	0.00	
beta_AF	-0.224	0.183	-1.23	0.22	*	0.184	-1.22	0.22	*
beta_AJ	0.938	0.0948	9.90	0.00		0.0953	9.85	0.00	
beta_C	-1.70	0.113	-15.03	0.00		0.118	-14.43	0.00	
beta_CE	0.745	0.114	6.52	0.00		0.117	6.39	0.00	
beta_D	-0.771	0.0881	-8.75	0.00		0.0911	-8.46	0.00	
beta_DH	0.544	0.104	5.21	0.00		0.103	5.26	0.00	
beta_E	-0.782	0.0917	-8.52	0.00		0.0962	-8.12	0.00	
beta_F	-1.52	0.117	-13.07	0.00		0.118	-12.91	0.00	
beta_G	-0.194	0.0792	-2.45	0.01		0.0852	-2.28	0.02	
beta_H	-1.17	0.110	-10.60	0.00		0.113	-10.32	0.00	
beta_HB	-1.93	0.187	-10.32	0.00		0.192	-10.02	0.00	
beta_I	-0.973	0.0914	-10.64	0.00		0.0967	-10.06	0.00	
beta_IK	0.803	0.0934	8.60	0.00		0.0941	8.54	0.00	
beta_J	-1.05	0.0909	-11.56	0.00		0.0936	-11.21	0.00	
beta_K	-1.43	0.0999	-14.28	0.00		0.102	-14.00	0.00	
beta_cp_A	0.316	0.0471	6.72	0.00		0.0488	6.48	0.00	
beta_cp_D	-0.0480	0.0556	-0.86	0.39	*	0.0604	-0.80	0.43	*
beta_cp_E	0.220	0.0588	3.75	0.00		0.0611	3.60	0.00	
beta_cp_F	0.237	0.0720	3.29	0.00		0.0732	3.24	0.00	
beta_cp_G	0.0512	0.0507	1.01	0.31	*	0.0553	0.92	0.36	*
beta_cp_H	-0.135	0.0708	-1.90	0.06	*	0.0769	-1.75	0.08	*
beta_cp_I	0.184	0.0563	3.27	0.00		0.0589	3.12	0.00	
beta_cp_J	0.354	0.0522	6.78	0.00		0.0536	6.61	0.00	
beta_cp_K	0.195	0.0565	3.45	0.00		0.0603	3.23	0.00	
beta_drive_D_AE	0.106	0.296	0.36	0.72	*	0.299	0.35	0.72	*
beta_drive_D_CN	-0.438	0.273	-1.60	0.11	*	0.283	-1.55	0.12	*
beta_drive_D_DK	0.280	0.248	1.13	0.26	*	0.253	1.11	0.27	*
beta_drive_D_US	0.0903	0.250	0.36	0.72	*	0.260	0.35	0.73	*

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
beta_female_A	0.166	0.0926	1.80	0.07	*	0.0933	1.78	0.07	*
beta_female_C	-0.0704	0.202	-0.35	0.73	*	0.204	-0.35	0.73	*
beta_female_C_AE	-0.535	0.270	-1.98	0.05		0.272	-1.97	0.05	
beta_female_C_CN	-0.131	0.234	-0.56	0.58	*	0.237	-0.55	0.58	*
beta_female_C_DK	-0.149	0.231	-0.64	0.52	*	0.236	-0.63	0.53	*
beta_female_C_US	0.0370	0.238	0.16	0.88	*	0.239	0.15	0.88	*
beta_female_D	-0.435	0.189	-2.30	0.02		0.199	-2.18	0.03	
beta_female_D_AE	-0.174	0.263	-0.66	0.51	*	0.262	-0.66	0.51	*
beta_female_D_CN	0.204	0.225	0.90	0.37	*	0.228	0.89	0.37	*
beta_female_D_DK	-0.0203	0.222	-0.09	0.93	*	0.230	-0.09	0.93	*
beta_female_D_US	0.207	0.228	0.91	0.36	*	0.237	0.87	0.38	*
beta_female_E	-0.0890	0.168	-0.53	0.60	*	0.170	-0.52	0.60	*
beta_female_E_AE	-0.549	0.220	-2.49	0.01		0.220	-2.49	0.01	
beta_female_E_CN	0.131	0.187	0.70	0.48	*	0.187	0.70	0.48	*
beta_female_E_DK	-1.02	0.222	-4.57	0.00		0.222	-4.58	0.00	
beta_female_E_US	-0.102	0.199	-0.51	0.61	*	0.201	-0.51	0.61	*
beta_female_F	-0.102	0.108	-0.95	0.34	*	0.111	-0.92	0.36	*
beta_female_G	-0.495	0.0722	-6.85	0.00		0.0783	-6.32	0.00	
beta_female_H	-0.0581	0.0968	-0.60	0.55	*	0.0980	-0.59	0.55	*
beta_female_I	-0.306	0.0814	-3.76	0.00		0.0845	-3.62	0.00	
beta_female_J	-0.288	0.0783	-3.67	0.00		0.0817	-3.52	0.00	
beta_female_K	-0.173	0.0840	-2.06	0.04		0.0875	-1.98	0.05	
beta_he_D_AE	-0.756	0.270	-2.80	0.01		0.276	-2.74	0.01	
beta_he_D_CN	-0.700	0.229	-3.06	0.00		0.232	-3.02	0.00	
beta_he_D_DK	-0.644	0.242	-2.65	0.01		0.245	-2.63	0.01	
beta_he_D_US	-0.678	0.242	-2.81	0.01		0.248	-2.73	0.01	
beta_he_H_AE	-0.121	0.292	-0.41	0.68	*	0.282	-0.43	0.67	*
beta_he_H_CN	0.560	0.252	2.22	0.03		0.244	2.30	0.02	
beta_he_H_DK	-0.107	0.289	-0.37	0.71	*	0.282	-0.38	0.70	*
beta_he_H_US	-0.673	0.303	-2.22	0.03		0.294	-2.29	0.02	
beta_he_I_AE	-1.15	0.240	-4.81	0.00		0.242	-4.77	0.00	
beta_he_I_CN	-0.404	0.197	-2.05	0.04		0.200	-2.02	0.04	
beta_he_I_DK	-0.609	0.225	-2.70	0.01		0.226	-2.69	0.01	
beta_he_I_US	-0.579	0.212	-2.73	0.01		0.216	-2.68	0.01	

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
beta_inc_A_AE	-9.22e-05	4.84e-05	-1.90	0.06	*	4.95e-05	-1.86	0.06	*
beta_inc_A_CN	-4.37e-05	4.29e-05	-1.02	0.31	*	4.28e-05	-1.02	0.31	*
beta_inc_A_DK	8.49e-06	4.43e-05	0.19	0.85	*	4.43e-05	0.19	0.85	*
beta_inc_A_US	-1.55e-05	4.39e-05	-0.35	0.72	*	4.36e-05	-0.36	0.72	*
beta_inc_D_AE	-1.46e-05	4.06e-05	-0.36	0.72	*	4.03e-05	-0.36	0.72	*
beta_inc_D_CN	7.30e-05	3.26e-05	2.24	0.03		3.29e-05	2.22	0.03	
beta_inc_D_DK	2.99e-05	2.88e-05	1.04	0.30	*	2.91e-05	1.03	0.30	*
beta_inc_D_US	4.87e-05	3.13e-05	1.56	0.12	*	3.19e-05	1.53	0.13	*
beta_inc_H_AE	7.88e-05	7.84e-05	1.01	0.31	*	7.94e-05	0.99	0.32	*
beta_inc_H_CN	-1.82e-05	3.80e-05	-0.48	0.63	*	3.77e-05	-0.48	0.63	*
beta_inc_H_DK	1.38e-06	3.91e-05	0.04	0.97	*	3.84e-05	0.04	0.97	*
beta_inc_H_US	1.30e-05	4.55e-05	0.29	0.77	*	4.47e-05	0.29	0.77	*
beta_inc_K_AE	-0.000100	4.32e-05	-2.32	0.02		4.44e-05	-2.26	0.02	
beta_inc_K_CN	-2.27e-05	3.84e-05	-0.59	0.55	*	3.82e-05	-0.59	0.55	*
beta_inc_K_DK	-3.30e-05	3.55e-05	-0.93	0.35	*	3.56e-05	-0.93	0.35	*
beta_inc_K_US	-3.21e-05	3.74e-05	-0.86	0.39	*	3.82e-05	-0.84	0.40	*
beta_threepolicy	-0.277	0.0474	-5.83	0.00		0.0375	-7.38	0.00	
beta_tran_C_AE	0.0379	0.484	0.08	0.94	*	0.497	0.08	0.94	*
beta_tran_C_CN	-0.463	0.389	-1.19	0.23	*	0.389	-1.19	0.23	*
beta_tran_C_DK	-0.446	0.396	-1.13	0.26	*	0.395	-1.13	0.26	*
beta_tran_C_US	-0.526	0.478	-1.10	0.27	*	0.483	-1.09	0.28	*