How do urban characteristics affect climate change mitigation policies?

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Abstract

Urban policy plays an important role in urbanization and urban sprawl, which in turn affect changes in CO_2 emissions from urban areas. However, urban planning policies that consider climate change mitigation have not been widely adopted, despite the issue's importance. To promote the consideration of climate change policies in urban planning, it is useful to identify the key determinants of effective climate change mitigation for policy makers. The objective of this study is therefore to identify the determining factors that affect changes in urban CO_2 emissions based on city type using a dataset of metropolitan areas. We obtained data on 276 cities in 26 countries for the years 2000, 2005, and 2008. We divided the data into five regional groups and four clusters to control for the characteristics of metropolitan areas. The dataset includes urban CO_2 emissions, GDP, and population. Three variables related to urban characteristics are subjected to determinants analysis using an econometric approach. The results show that the determinants of changes in urban CO_2 emissions differ by city type and region. These results contribute to a better understanding of urban policies that can improve the effects of these driving factors by considering the characteristics of each city type.

1. Introduction

Urban policy plays an important role in urbanization and urban sprawl, which in turn affect changes in greenhouse gas (GHG) emissions from urban areas (Hendrickson et al. 2016). According to Fragkias (2013), 60%–80% of global energy use was consumed in urban areas in recent years, and more than 70% of global GHG emissions are produced within urban areas. The OECD (2014) noted that cities can play a key role in addressing global climate change through smart urban design and planning.

Given this situation, urban climate mitigation activities have been promoted by city leaders to protect their cities against the threat of natural disasters (Rosenzweig et al., 2010). The World Mayoors Council on Climate Change (WMCCC) was founded in 2005 to strengthen cities' commitment to climate change mitigation. In January 2017, 88 members of the council developed a network of local government activities that can reduce GHG emissions. In addition, non-party stakeholders[1] including city and local governments are required to scale up their climate mitigation activities with the adoption of the Paris agreement (UNFCCC, 2015).

However, urban policies that consider climate change mitigation have not been widely adopted (Broto and Bulkeley, 2013; OECD, 2014), and the trade-off relationship between climate mitigation and economic competitiveness or social issues is one major reason (Viguié and Hallegatte, 2012). Therefore, the balance between economics, social issues, and the environment is an important factor in developing urban sustainability policies because the economic and social situation critically affects the employment ratio and governmental budget resources, which are key components in urban development.

With the increased attention on urban climate policies, the number of studies that focus on urban planning for climate change mitigation and adoption has grown in recent years (Davoudi et al. 2010; Broto, 2017). McDonald et al. (2011) focus on the effects of climate change on future fresh water availability and urban water resources in developing countries. Wamsler et al. (2013) propose a conceptual framework for a city disaster nexus that includes urban risk reduction and adaptation strategies for climate change.

Some studies focus on a case study of a specific area. Hendrickson et al. (2016) apply life cycle

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[1] Accroding to the UNFCCC (2015), non-party stakeholders include civil society, the private sector, financial institutions, cities and other sub-national authorities, local communities and indigenous peoples.

assessment to evaluate San Francisco's climate change mitigation strategy. Lee and Painter (2015) compare the urban climate change mitigation policies in four cities—Seoul, Busan, Seattle and Anaheim. Damsø et al. (2016) examine the climate action plans of local governments by focusing on the mitigation target level and scope of GHG accounts in Denmark.

There are many studies that analyse urban climate policies and mitigation activities, but few have investigated the key determinants of effective urban climate change mitigation using a large amount of data on metropolitan areas. Additionally, previous studies use cross-country or multiple-city data to identify the key determinants and do not clearly consider the differences in the characteristics of cities and the sources of CO_2 emissions, which can significantly affect the determinants of changes in urban CO_2 emissions.

Lee and Painter (2015) and Mi et al. (2017) note that cities vary in their procedures for planning and implementing GHG mitigation policies. Dabo et al. (2016) clarify the diversity of the residential carbon footprint among income groups, which strongly affects consumer choice. Additionally, the characteristics of cities are diverse because many conditions differ, including geographies, core industrial sectors, and climate conditions (Fujii and Managi, 2016a; Meng et al., 2017). Therefore, cities implement different urban policies because they have different characteristics, and these characteristics must be considered when analysing appropriate urban planning policies and solutions for climate change mitigation.

Major GHG emissions sources differ among cities due to the cities' characteristics and available energy sources (UNEP, 2012). Figure 1 shows a scatterplot of the share of CO_2 emissions in the energy and transport sector for 276 metropolitan areas in 2008[2]. As shown in Figure 1, the main sources of CO_2 emissions differ among cities. UNEP (2012) notes that climate change mitigation efforts should be consistent with the desired solutions for major CO_2 emitting sectors in cities. Thus, effective climate change mitigation policies differ among cities that have different sources of CO_2 emissions.

<Figure 1 about here>

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[2] The energy sector includes public electricity, heat production, and other energy industries. The transport sector includes road, rail, and ground transportation.

2. Literature Review

There are multiple potential CO_2 emissions sources in cities, such as the transport, industrial, household, commerce and energy sectors, because a city's economic activities are diverse. Additionally, the characteristics of cities are diverse because many conditions differ, including geographies, core industrial sectors, and climate conditions (Fujii and Managi, 2016a; Meng et al., 2017). Therefore, a number of studies from various academic fields have examined the relationship between city characteristics and the CO_2 emissions from corresponding sectors.

When urban forms are changed, including new construction of infrastructure, the most influenced emissions source is the transportation sector because the flows of people and the logistics are changed. Noman et al. (2006) conclude that the most important target for reducing CO_2 emissions is the transport sector. One of the most well-known studies from the first era of such studies is Newman and Kenworthy (1989). Using data from large cities around the world from 1980, they show that per capita gasoline consumption (i.e., CO_2 emissions from vehicles) is higher in low density cities than in high density cities. However, the authors do not consider the other social and economic factors that can influence consumption. Glaeser and Kahn (2010) account for social and economic factors in their analysis and find that CO_2 emissions from vehicles are negatively correlated with population density based on data from 66 large cities in the United States. Using Japanese city data from 1990 to 2010, Iwata and Managi (2016) show the same relationship and conclude that urban policies such as property taxes and land use regulations can be used to increase population densities, thereby reducing CO_2 emissions from vehicles.

With regard to the household sector, Makido et al. (2012) define an index of city complexity and compare 15 Japanese cities using data from 2005. They find that residential per capita CO_2 emissions are lower in less complex cities than in highly complex cities. Analysing 30 provincial capital cities in China, Fang et al. (2015) support the reduction of complexity as a measure for climate change mitigation. Ahmad et al. (2015) analyse approximately 19,000 households' CO_2 emissions data in India, including electricity and cooking, and show that households in high density cities are likely to have lower CO_2 emissions than in low density cities. Noman et al. (2006) divide the Toronto metropolitan area into low and high density areas and compare three types of per capita CO_2 emissions (i.e., transportation, building operations and building materials). The authors conclude that all three types of per capita CO_2 emissions are lower in high

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density areas than in low density areas. Therefore, urbanization helps to reduce residential CO_2 emissions, not only in developed countries but also in developing counties.

Instead of analysing different sectors' CO_2 emissions, several studies employ a top-down approach, that is, they examine the relationship between the urban form and total CO_2 emissions. Marcotullio et al. (2012) extract data for 3,535 urban areas from 45 Asian countries and find that total CO_2 emissions in urban areas are negatively associated with population density. Using a large dataset from 40 countries in Europe that covers 1,153 cities with more than 50,000 residents, the same research team, Marcotullio et al. (2014), modify the STIRPAT model to examine the determinants of total CO_2 emissions. The results show that population density is strongly and negatively associated with emissions. Alli et al. (2017) examine the relationship between urbanization (i.e., urban population) and total CO_2 emissions using a long-term dataset from 1970 to 2015 in Singapore, a unique island-city-country. Their main finding is that urbanization is negatively and significantly correlated with emissions. These studies also imply that the promotion of urbanization and increases in population density can mitigate climate change by reducing CO_2 emissions from the household sector.

The literature advocates urban policies such as those described above for combatting climate change. However, some studies reveal different relationships. Zhang and Lin (2012) divide China into eastern, central and western regions and separately analyse the relationship between urbanization (i.e., the share of the urban population) and total CO_2 emissions. Using provincial panel data from 1995 to 2010, they find heterogeneous effects of urbanization on total CO_2 emissions. In particular, a positive relationship is found in the central region, suggesting that urbanization worsens climate change, and therefore the appropriate urban policies are not the same among regions. This finding is in line with the conclusion of Meng and Huang (2017). In addition, Liddle (2014) mainly reviews prior studies using macro/country-level data and finds that recent studies reach diverse conclusions.

The diverse conclusions in the literature must be a result of the complexity of cities' forms and functions as well as the diversity of geographic, climatic, social, and cultural characteristics among cities and countries, which implies that we should tailor urban policies based on the situation in each city and country. When analysing the relationship between the city form and CO_2 emissions, most recent studies control for not only socio-economic factors but also geographic and climate conditions. However, few

studies consider the structure of emissions sources. For example, most studies do not explicitly distinguish among cities with high shares of CO_2 emissions in the energy industry and in the transportation industry. Therefore, in parallel with controlling for socio-economic, geographic and climate factors, we overcome this gap in the literature by employing a cluster analysis, which will be explained in section 3.1. Then, we employ determinants analysis in order to identify tailored urban policies.

Given this background, the objective of this study is to identify the determining factors that affect urban CO_2 emissions and intensity based on city type using a dataset of metropolitan areas from the OECD.stat database. We obtain data for 276 cities in 26 countries for the years 2000, 2005, and 2008. The dataset includes urban CO_2 emissions, GDP, and population. These three variables are applied to the decomposition analysis. Additionally, data on compact city and urban policy variables are applied to the determinants analysis using an econometric approach (see Figure 2). Because the characteristics of cities are diverse, we divide the sample by city type and focus on the share of CO_2 emissions from the energy industry, transport, and other sources using cluster analysis, which reflects a determinants approach to identifying the driving factors of changes in urban CO_2 emissions and intensity based on city characteristics.

<Figure 2 about here>

3. Data and Methodology

3-1. Data sample and grouping

We obtained urban CO_2 emissions and social data from the database of metropolitan areas in OECD.stat (OECD, 2012). This database covers 281 metropolitan areas with a population of 500,000 or more in 30 OECD countries for the years 2000, 2005, and 2008.[3] Because GDP data for five metropolitan areas (Oslo,

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[3] According to the OECD (2012), the estimation of CO_2 emissions data uses the EDGAR global emissions database (version 4.1), which was developed by the Joint Research Centre of the European Commission. The methodology employed essentially sums the EDGAR estimated values for 0.1-by-0.1 degree grids over the relevant boundaries of the metropolitan areas.

Zurich, Geneva, Basel, and Copenhagen) are unavailable from OECD.stat, we excluded them from the dataset. Thus, we used data on 276 metropolitan areas, which are listed in Appendix 1.

We divided the data on the 276 cities into five regional groups (see Appendix 1) and four clusters in order to understand the effects of a metropolitan area's characteristics. In the regional grouping, the first group is the U.S. region, where people mainly use automobiles over long distances. The second group is the EU, which has produced an advanced urban planning policy for environmental protection. The third group is Japan and Korea (JP&KR), which has high population density. The fourth group is Australia and Canada (AU&CA), which have large land areas and low population density. The fifth group is Chile and Mexico (CL&MX), which are developing countries.

As shown in Figure 2, this study applies a three-step approach to investigate the determinants of changes in urban CO_2 emissions by city type. First, we apply a k-means partition cluster analysis for the share of CO_2 emissions in each sector to identify the urban CO_2 emissions characteristics. The advantage of a k-means partition cluster analysis is that it can treat a large dataset using a concise algorithm better than other types of cluster analysis (Li et al., 2016). K-means partition cluster analysis is widely applied in research fields related to urban economics and urban planning (Chévez et al., 2017). Figure 3 shows the results of the cluster analysis using the share of CO_2 emissions from the energy industry, transport, and other sectors.

<Figure 3 about here>

In Figure 3, we can see the characteristics of each cluster group. Cluster 1 tends to have a high share of CO_2 emissions in the energy industry and a low share in the transport sector. Meanwhile, the cities in cluster 3 have high shares of CO_2 emissions in the transport sector and low shares in the energy industry. Thus, these two clusters have the opposite characteristics with regard to the main CO_2 emissions source. Additionally, the cities in cluster 2 tend to be close to the origin, which means that the share of CO_2 emissions in the other sector is high. Cluster 4 maintains a balance in the share of CO_2 emissions from the three sectors. Based on these results, we call cluster 1 (C1) the energy-industry-oriented group, cluster 2

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(C2) the other-sector-oriented group, cluster 3 (C3) the transport-sector-oriented group, and cluster 4 (C4) the balanced group.

3-2. Variables

Table 1 shows the variables and their descriptions. CO_2 emissions data are available for three types of variables: [1] CO_2 emissions per capita, [2] CO_2 emissions per capita from the energy industry, and [3] CO_2 emissions per capita from transport. We create the category "CO_2 emissions per capita from other sectors" using the above three variables (see definition in Table 1). Additionally, we generate variables for the share of CO_2 emissions from each sector for the cluster analysis.

<Table 1 about here>

We can decompose the CO_2 emissions intensity (INTENSITY), defined as CO_2 emissions per unit of GDP, using the following equation:

$$INTENSITY = CO_2/GDP = CO_2per / GDPper. \qquad (1)$$

In this case, INTENSITY is defined by the ratio between CO_2 emissions per capita and GDP per capita. If the scale of economic activity declines, CO_2 emissions will decrease due to the scaling down of production, and consumption behaviour and GDP will decrease (Fujii and Managi, 2016b). As a result, INTENSITY is not greatly affected by a change in the economic situation. Thus, INTENSITY controls for the effect of changes in the economic situation caused by business cycles.

Many studies focus on the relationship between economic development (i.e., GDP per capita) and CO_2 emissions per capita, although a clear relationship has not been observed[4]. Thus, GDP per capita and CO_2 emissions per capita do not have a clear trade-off or proportional relationship. Based on this

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[4] For example, environmental Kuznets curves for city data (Wang and Ye, 2016), OECD countries (Fujii and Managi, 2013), and global data (Dong et al., 2016) .

background, we assume that GDP per capita and CO_2 per capita can be independently changed. In this case, the identification of the determinants of each driving factor is important in order to construct an effective and appropriate urban policy for GDP per capita growth and CO_2 per capita reduction.

Another benefit of applying a decomposition framework is to distinguish among the effects of the determinant variables. Based on equation (1), there are several ways to decrease INTENSITY. One way is to decrease CO_2 emissions per capita while maintaining GDP per capita, while another way is to increase GDP per capita while maintaining CO_2 emissions per capita. To investigate the relationship between the decomposed variables and the determinants, we can examine the influence path of each determinant of INTENSITY by considering the coefficients of the determinants for each decomposed factor (see Figure 2).

As explained in Table 1, DENS, COMM, and CORE are applied as determinant variables of urban CO_2 intensity. Previous studies have attempted to capture urban characteristics using a variety of variables (see Table 1 in Bhatta et al. (2010) and Table 1 in Siedentop and Fina (2010)). We follow the theory and framework for urban data specifications constructed in previous studies. Here, we explain the reason for the choice of determinant variables with reference to the previous literature.

First, we use DENS as the degree of agglomeration in metropolitan areas. According to Melo et al. (2009) and Uchida and Nelson (2010), population density is a key variable for evaluating urban agglomeration. Fritsch and Mueller (2008) note, "One of these variables is population density or degree of agglomeration". Thus, we apply DENS as a proxy variable for urban agglomeration.

Next, we apply COMM as the degree of urban sprawl. Wolman et al. (2005) analyse urban sprawl by focusing on a commuting data variable. Holcombe and Williams (2010) state, "A most common complaint of sprawling development is that it lengthens commuting times". Thus, there is a strong relationship between commuting time and urban sprawl. Based on these studies, we use COMM as a proxy variable for urban sprawl.

It should be noted that the different methods of commuting could lead to differences in CO_2 emissions. For example, transit-oriented development, which refers to the idea of integrating transit and land use by focusing development around transit stations, can achieve a good balance between urban

sprawl and CO_2 emissions reduction due to a high rate of public transportation usage (OECD, 2015). However, data on the utilization of public transportation are not available. Thus, it is difficult for us to investigate the methods of commuting in each metropolitan area. Based on this data limitation, this study used the degree of urban sprawl.

Finally, the CORE variable is used as the degree of compactness. In contrast to COMM, which evaluates urban sprawl by focusing on a specific area, CORE measures the degree of compactness using the population distribution. According to the OECD (2012), the population over the surface of urban land within a metropolitan area, which is the definition of CORE, can be introduced as a proxy variable for urban compactness.

3-3. Determinants analysis

To identify effective urban policies to mitigate climate change for each cluster and region, we employ regression analysis. That is, we regress CO_2 emissions intensity on the three determinant factors (see Table 1) for each cluster. Therefore, we perform 5 estimations (i.e., 4 clusters + all observations). In addition, we allow heterogeneous effects of each determinant factor among regions because there is a high degree of diversity with regard to cultural and social backgrounds among the regions. We use the interaction terms of a regional dummy (i.e., R) and three determinant factors instead of the simple determinant factors. The specification for the regression is assumed to be as in the following equation (2):

$$\text{INTENSITY}_{ijkt} = \alpha + \sum_i \beta_{0i} \cdot R_i \cdot DENS_{ijkt} + \sum_i \beta_{1i} \cdot R_i \cdot COMM_{ijkt} + \sum_i \beta_{2i} \cdot R_i \cdot CORE_{ijkt} + \mu_t +$$
$$\delta_j + \varepsilon_{ijkt} \ . \quad (2)$$

The subscripts i, j, k and t denote region, country, city and time, respectively, whereas α and β_{0i}, β_{1i}, and $\beta_{2i}(i = 1, \dots, 5)$ are parameters. Therefore, 16 parameters are estimated in each regression. The unobserved time- and country-specific effects are captured by μ_t and δ_j, respectively. The idiosyncratic error term is expressed as ε_{ijkt}.

The country-specific effects capture the effects of countries' time-irrelevant characteristics such as geographic, climatic, social and cultural conditions. Additionally, the time-specific effects control for

country-irrelevant time effects such as economic fluctuations throughout the world. We apply these two specific effects to control for the effects of country and time differences in our estimation.

Dynamic panel data analysis (e.g., generalized method of moments) is an alternative model for determinants analysis using panel data. However, dynamic panel data analysis needs to have a two-year lag for the estimation (Arellano & Bond, 1991). Because our dataset covers only three years, it is difficult to establish a two-year lag for the estimation using a fixed effects model. However, the use of a fixed effects model that employs country- and time-specific effects is important to control for the characteristics of metropolitan areas in the determinants analysis. Thus, we select a regression model with a specific effects term based on the situation for our dataset and its relevance to our research objective. This aspect is a limitation of this study.

4. Results

4-1. Determinants analysis of changes in urban CO_2 intensity

Table 2 presents the results of the determinants analysis using INTENSITY as the dependent variable. In addition to Table 2, we describe the results of the determinants analysis using CO_2 per capita and GDP per capita as the dependent variables in Appendix 2 and Appendix 3, respectively. In these tables, we show the results of five models, including the entire sample (276 cities), using city data in each cluster. We use three determinant variables with a cross-term of regional dummy variables.

One advantage of the cross-term with regional dummies approach is the direct comparability of the coefficient score among regions with the same determinant variables. Therefore, the differences in the effects of the determinant variables on carbon intensity can be identified by comparing the coefficient values of the cross-terms. Furthermore, the combination of independent variables is the same in the five models (e.g., all-sample model, cluster 1 model). Therefore, we can also directly compare the coefficient scores among the models.

As shown in Table 2, the coefficient scores of the three determinant variables differ among the regions and cluster groups. The results indicate that the three determinant variables affect INTENSITY differently among the regional groups and clusters. It should be noted that we observed many cases in

which the sign of the coefficient score is the opposite with regard to the results of the all-sample model and that of each cluster model. These results imply that the effects of the determinant variables on INTENSITY change when we consider the characteristics of urban CO_2 emissions sources. This finding provides important evidence that urban policies that are based on empirical studies that do not consider urban CO_2 emissions characteristics might be misleading with regard to urban CO_2 mitigation.

Table 2 shows that all cross-terms between the three determinant variables and the U.S. dummy significantly affect INTENSITY. One interesting result is that the cross-term between CORE and the U.S. dummy positively affects INTENSITY in the all-sample model. This result implies that a decreasing concentration of the population in the core area contributes to reduced INTENSITY, regardless of the urban CO_2 emissions sources in the U.S. The coefficient score of the cross-term between CORE and the U.S. dummy differs among the cluster models. The result of the cluster 2 model shows the largest coefficient score, and the result of cluster 4 is the smallest. Therefore, the expected INTENSITY reduction effect due to a CORE decline is stronger in cities in cluster 2 than the others.

<Table 2 about here>

Additionally, the cross-term between the U.S. dummy and COMM showed the opposite coefficient sign in the all-sample model and the cluster 1 model. One interpretation of this result is that the main CO_2 emissions source is the energy industry in the cluster 1 city group. The amount of CO_2 emissions from the energy industry is usually directly related to the scale of electricity demand and the energy mix for power generation. However, this is not directly related to the urban structure, including the commuting zone, which may be one reason for the opposite coefficient sign between the all-sample and cluster 1 models.

Next, we discuss the other regional dummy results. The cross-term between DENS and the CL&MX dummy has a significantly positive effect on INTENSITY in all cluster models except for cluster 4. In contrast to this result, the cross-term between CORE and CL&MX has a significantly negative effect on INTENSITY in the cluster 2 and cluster 3 models. These results indicate that effective urban policies to decrease INTENSITY are decreased density and increased concentration for cities grouped in clusters 2 and 3 in Chile and Mexico. Detailed urban policy options will be discussed in the next section.

4-2. Urban policy options for CO_2 emissions mitigation

Next, we consider the determinants analysis results by focusing on two driving factors of INTENSITY (see Figure 2). Appendix 4 summarizes the determinants analysis results using INTENSITY, CO_2 per capita, and GDP per capita as the dependent variables (detailed results are shown in Table 2 and in Appendix 2 and Appendix 3). As shown in Appendix 4, the significance levels and signs of the coefficient scores differ among the country dummies and cluster groups.

We can identify the most desirable combination of coefficient scores by referring to Appendix 4. If we observe the combinations in which the determinant variable negatively (positively) affects INTENSITY and CO_2 per capita and positively (negatively) affects GDP per capita, then decreasing (increasing) the determinant variables decrease INTENSITY by decreasing CO_2 per capita and increasing GDP per capita simultaneously. We explain this approach using the results of the cross-term between the three determinant variables and the U.S. dummy. Table 3 presents the desirable change in the determinant variables identified in Appendix 4. In Table 3, "Increase" shows that increasing the determinant variable score is a desirable way to decrease INTENSITY and CO_2 per capita and to increase GDP per capita. In contrast, "Decrease" suggests that decreasing the determinant variable score is a desirable approach.

It is important to consider that the suggested urban policy should be consistent with managerial insights from urban planning. In other words, urban policy makers will not refer to a suggested urban policy if it will decrease the flexibility of land use and the attractiveness of the city. From an economic perspective, it is well known that policy options using market mechanisms are more flexible and efficient than restrictive policies (e.g., command and control) (Iwata and Managi, 2016). Based on this idea, we propose policy options that focus on market mechanisms such as property taxes.

<Table 3 about here>

As shown in Table 3, an increase in DENS and a decrease in CORE are a desirable means of reducing INTENSITY. To achieve these changes to these determinant variables, property taxes are one effective urban policy option. According to Brueckner and Kim (2003) and Song and Zenou (2006), a decrease (increase) in property taxes promotes population inflow (outflow). Therefore, an increase in

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property taxes over an entire metropolitan area can be expected to increase the population density. In addition to this policy, further increasing property taxes in the core area would contribute to decreasing the population concentration in this area. The combination of these two urban policy options is proposed based on the results of the determinants analysis.

However, we should note that the desirable determinant variable change differs between the all-sample model and cluster 2. Therefore, the above policy options would be helpful for cities in the U.S. except for those in cluster 2. This differing trend provides important evidence regarding the importance of developing urban climate policy while considering city characteristics because an urban policy that refers only to the all-sample results would have undesirable effects in cities with unique characteristics with regard to urban climate change mitigation. One advantage of determinants analysis in combination with cluster analysis is the ability to identify desirable urban policy options for cities that have different trends from the entire sample.

As shown in Table 3, decreasing both DENS and COMM produces a desirable variable change to decrease INTENSITY and CO_2 per capita with increased GDP per capita in cluster 2. One policy option for decreasing the commuting area is land use regulations. Banzhaf and Lavery (2010) note that an increase in land (split) taxes exerts a more constraining influence on city size (urban sprawl) than an increase in property taxes. Iwata and Managi (2016) clarify that property taxes and land use regulations clearly affect population density. To restrict suburban living by applying these land tax and land use regulations, governments can create urban commuting zones.

Finally, cluster 3 shows that the combination that produces the most desirable determinant change involves increasing COMM and decreasing CORE. Because the main CO_2 emissions source in cluster 3 is the transport sector, the highly concentrated core areas in cities in this cluster tend to lead to traffic congestion due to the prevalence of commuting by private car. According to INRIX (2017), New York and San Francisco, which are categorized as cities in cluster 3, have been identified as the third and fourth worst cities in the world for traffic congestion. This result provides further evidence that cities in cluster 3 tend to suffer from traffic congestion.

Based on this information, we can suggest an expansion of public transportation services in order to expand the commuting zone. In addition to this urban policy, increasing the property taxes in core areas would contribute to decreasing the population concentration in those areas. An alternative urban policy to decrease traffic congestion is to increase the incentives to use public transportation, such as by introducing additional customer services (Zhang et al, 2014).

5. Conclusions

This study examined the determinant factors that contribute to changes in urban CO_2 emissions intensity by considering the city characteristics of the main CO_2 emissions sources. We use data from 276 metropolitan areas in 26 countries from 2000, 2005, and 2008. This study divides the sample into five regional groups and four clusters based on CO_2 emissions sources in order to control for the specific characteristics of metropolitan areas. In this study, a research framework was proposed that combined three approaches: decomposition analysis, cluster analysis, and determinants analysis.

We find that the determinants of the driving factors of changes in urban CO_2 emissions differ by city cluster type and region. Our estimation results indicate that a decreasing concentration of the population in the core area contributes to reduced CO_2 emissions per capita regardless of urban CO_2 emissions sources in the U.S. On the other hand, there are many cases in which the sign of the coefficient is the opposite with regard to the results of each cluster sample and the results of all-sample model.

These findings indicate that urban policies based on empirical analyses that do not consider the portfolio of urban CO_2 emissions sources might be misleading with regard to urban CO_2 mitigation. This result implies that we can implement better urban policies to improve each factor by considering the characteristics of each city type.

Currently, many local governments have designed environmental policies to reduce urban CO_2 emissions. The novel contribution of the present study is the development of a research framework to identify the determinants of changes to urban CO_2 emissions. The research framework and the application of the decomposition and econometric analyses for urban CO_2 emissions changes may be helpful in

evaluating the determinants of urban CO_2 emissions, which can contribute to building effective urban planning strategies and environmental policies.

Further research is needed to investigate the following three aspects. First, to reduce urban CO_2 emissions, it is useful to identify the appropriate partnerships between local and national governments because both urban planning by both levels of government influences urban CO_2 emissions. This argument is similar to that regarding the issue of effective carbon rates (OECD, 2016). Second, it is necessary to focus on different pollutants (e.g., a determinants analysis of urban air pollution substances) and to provide key information for urban air pollution management in order to protect human health (Zhang et al., 2017). Third, it is important to consider new technologies and people's preferences (e.g., smart cities and a sharing economy) for desirable urban policy designs (Cohen and Muñoz, 2016).

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Table 1. Data description

	Variable (code)	Definition	unit	Mean value	Std. dev.
CO_2 emissions and driving factors	CO_2 emissions per capita (CO$_2$per)	CO_2 emissions (CO_2) divided by population	Tons CO_2/ person	10.63	7.60
	GDP per capita (GDPper)	GDP of metropolitan area divided by population	US $	37,226	15,389
	CO_2 emissions per GDP (INTENSITY)	CO_2 emissions divided by GDP of metropolitan area	Tons CO_2/ million US $	284.37	171.05
Data for cluster analysis	CO_2 emissions from energy industry(CO_2^{ene})	CO_2 emissions from energy industry	Million tons CO_2	4.62	7.89
	CO_2 emissions from transport (CO_2^{tr})	CO_2 emissions from transport sector	Million tons CO_2	5.84	12.75
	CO_2 emissions from other sectors (CO_2^{other})	$CO_2 - (CO_2^{ene} + CO_2^{tr})$	Million tons CO_2	10.01	18.64
	Share of CO_2 emissions from energy industry	CO_2^{ene} / CO_2	%	21%	23%
	Share of CO_2 emissions from transport	CO_2^{tr} / CO_2	%	29%	13%
	Share of CO_2 emissions from other sectors	CO_2^{other} / CO_2	%	50%	18%
Determinant factors	Population density of metropolitan area (DENS)	Population / metropolitan area	persons / km^2	670.94	740.27
	Commuting zone share (COMM)	Commuting zone land share over metropolitan area	%	60.38	29.25
	Concentration of population in the core (CORE)	Share of population living in the core area over the total metropolitan population	%	75.40	17.58

Source: Figure created by author using metropolitan area data from OECD.stat (OECD, 2013)

Note 1: Monetary data are deflated year 2010 prices.

Note 2: The energy sector includes public electricity, heat production, and other energy industries. The transport sector includes road, rail, and ground transportation. The "other" sector includes agriculture, manufacturing, services, and residential sectors (OECD, 2013).

Note 3: The core area and commuting zone are identified by the OECD (2013). The identification flow and detailed explanations are described in "Annex A: Defining regions and functional urban areas" and Figure A.5.

Table 2. Results of determinants analysis (dependent variable is INTENSITY [=CO_2/GDP])

VARIABLES	All sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4
AU&CA×DENS	-0.000729***	0.00258	0.000196***	N.A.	0.0186***
AU&CA×COMM	-0.0101***	0.146***	0.000789	N.A.	-0.235***
AU&CA×CORE	-0.00179	0.376***	0.000811	N.A.	0.267***
CL&MX×DENS	7.70e-06***	0.000293***	1.31e-05***	2.57e-05***	0.000293
CL&MX×COMM	0.000266*	0.0134***	-0.000560	-6.24e-05***	0.00873
CL&MX×CORE	-0.00425***	0.0243***	-0.0111*	-0.00654***	-0.00288
EU×DENS	-6.61e-05*	-0.000192***	1.15e-05	1.98e-05	5.71e-05
EU×COMM	-0.00511***	-0.00844***	-0.00187***	-0.000531	-0.00458
EU×CORE	-0.00146*	-0.00274	-0.00126	0.00112	0.00293***
JP&KR×DENS	3.48e-05***	-4.13e-05	7.05e-06	N.A.	-6.59e-05***
JP&KR×COMM	-0.00244	-0.00498*	0.000997**	N.A.	-0.00117***
JP&KR×CORE	-0.00484**	-0.00416	0.00151	N.A.	0.00198***
US×DENS	-0.000122***	-9.26e-05***	0.000215***	-4.33e-06***	-0.000232***
US×COMM	-5.83e-05***	0.00182***	0.000670***	-0.000664***	-0.00116***
US×CORE	0.000691***	0.00102***	0.00241***	0.000841***	0.000134***
2005 year dummy	-0.0258***	-0.0228	-0.0259***	-0.0220***	-0.0331**
2008 year dummy	-0.0488***	-0.0588*	-0.0447***	-0.0379***	-0.0594***
Constant	1.426**	-2.258***	0.0363	0.0563	0.162***
Observations	828	162	291	180	195
R-squared	0.292	0.640	0.737	0.474	0.512

Note 1: *denotes significance at 10% level, **denotes significance at 5% level, ***denotes significance at 1% level.

Note 2: "N.A." indicates that there is no sample selected, as in cluster 3 in the AU&CA and JP&KR region groups.

Table 3. Desirable determinant variable changes and policy options for cities in the U.S.

	DENS	COMM	CORE	Desirable urban policy option
All	**Increase**	N.A.	**Decrease**	-Decrease property taxes for metropolitan area -Increase property taxes for core area
Cluster 1	N.A.	N.A.	N.A.	N.A.
Cluster 2	**Decrease**	**Decrease**	N.A.	-Increase property taxes for metropolitan area -Land use policy for suburban area
Cluster 3	N.A.	**Increase**	**Decrease**	-Expand the public transportation area -Increase property taxes for core area
Cluster 4	N.A.	N.A.	N.A.	N.A.

Note: "Increase" indicates that the determinant variable negatively affects INTENSITY and CO_2 per capita and positively affects GDP per capita. "Decrease" indicates that the determinant variable positively affects INTENSITY and CO_2 per capita and negatively affects GDP per capita. "N.A." indicates that the coefficient scores of the determinant variable do not observe the above combination.
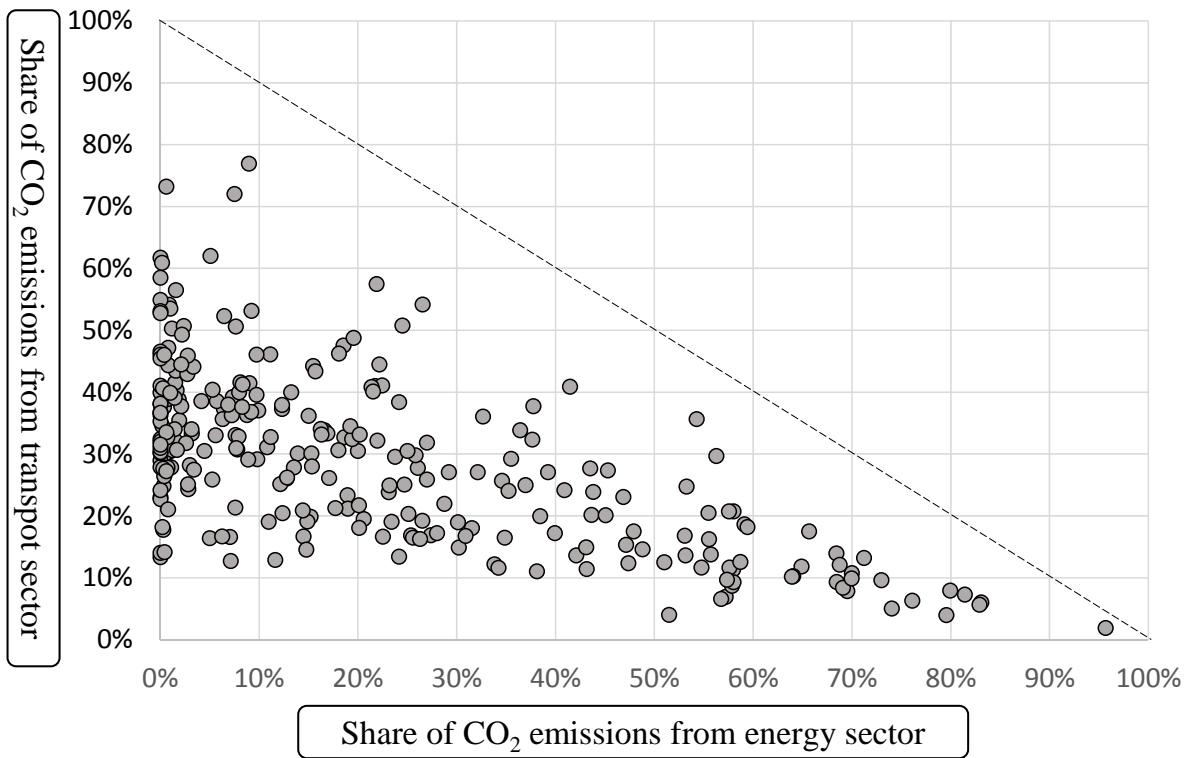
Figure 1. Scatterplot of CO_2 emissions share in energy and transport sectors in 2008

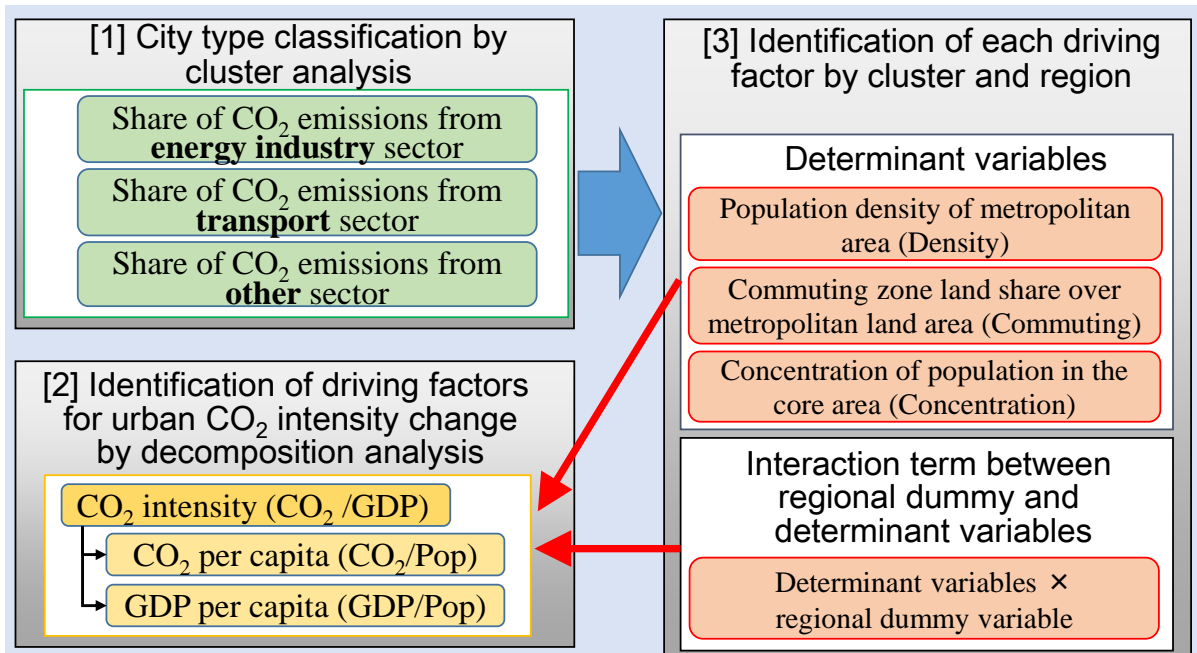Source: Figure created by author using metropolitan area data from the OECD.stat database

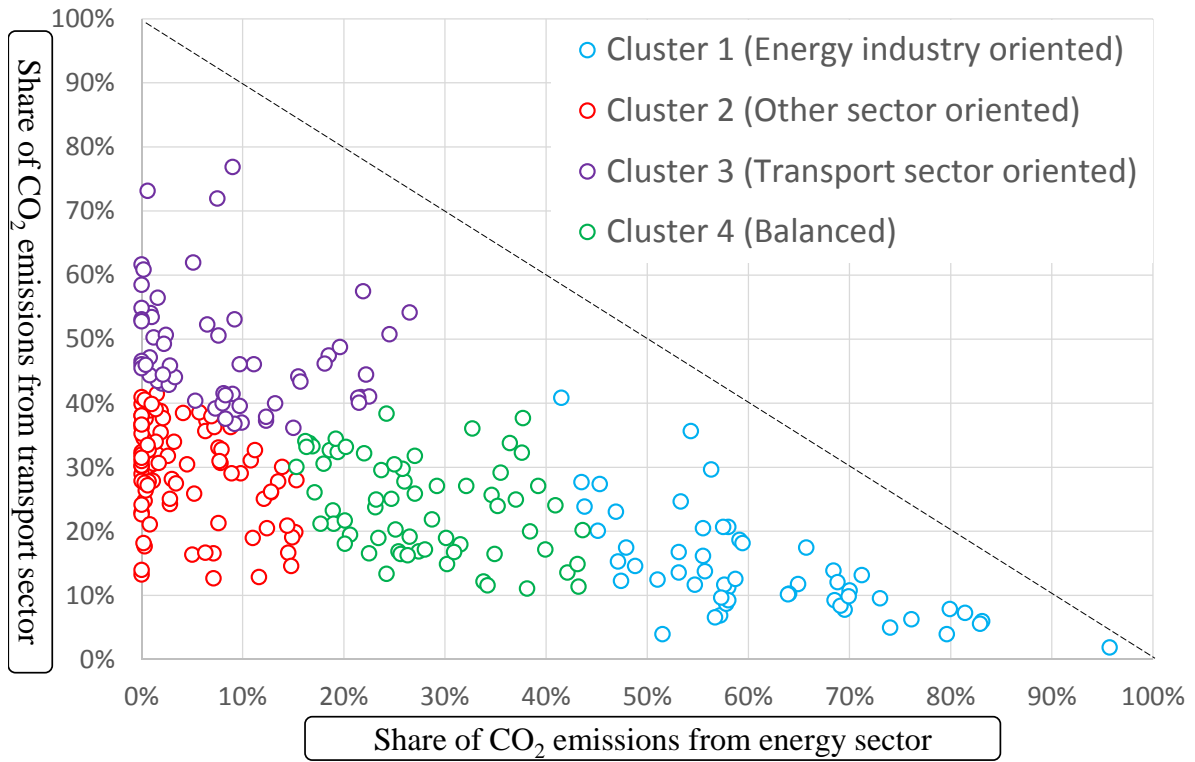Figure 2. Research framework of this study

Figure 3. Results of cluster analysis for the share of CO_2 emissions using year 2008 data

Appendix 1-1. Metropolitan area names and region groups

Metropolitan area name	Country	Country	Group	Metropolitan area name	Cluster	Country	Group
Sydney	2	Australia	AU&CA	Sapporo	2	Japan	JP&KR
Melbourne	2	Australia	AU&CA	Sendai	2	Japan	JP&KR
Brisbane	4	Australia	AU&CA	Niigata	2	Japan	JP&KR
Perth	2	Australia	AU&CA	Toyama	1	Japan	JP&KR
Adelaide	2	Australia	AU&CA	Nagano	2	Japan	JP&KR
Gold Coast-Tweed Heads	2	Australia	AU&CA	Kanazawa	2	Japan	JP&KR
Edmonton	1	Canada	AU&CA	Utsunomiya	2	Japan	JP&KR
Calgary	2	Canada	AU&CA	Maebashi	4	Japan	JP&KR
Winnipeg	2	Canada	AU&CA	Mito	2	Japan	JP&KR
Vancouver	2	Canada	AU&CA	Tokyo	4	Japan	JP&KR
Quebec	2	Canada	AU&CA	Kofu	2	Japan	JP&KR
Montreal	2	Canada	AU&CA	Nagoya	4	Japan	JP&KR
Ottawa-Gatineau	2	Canada	AU&CA	Numazu	2	Japan	JP&KR
Toronto	2	Canada	AU&CA	Osaka	4	Japan	JP&KR
Hamilton	1	Canada	AU&CA	Shizuoka	2	Japan	JP&KR
Valparaíso	2	Chile	CL&MX	Anjo	1	Japan	JP&KR
Santiago	2	Chile	CL&MX	Yokkaichi	1	Japan	JP&KR
Concepción	4	Chile	CL&MX	Himeji	1	Japan	JP&KR
Mexicali	1	Mexico	CL&MX	Toyohashi	2	Japan	JP&KR
Tijuana	2	Mexico	CL&MX	Hamamatsu	2	Japan	JP&KR
Juárez	1	Mexico	CL&MX	Okayama	2	Japan	JP&KR
Hermosillo	1	Mexico	CL&MX	Kurashiki	4	Japan	JP&KR
Chihuahua	1	Mexico	CL&MX	Fukuyama	2	Japan	JP&KR
Reynosa	1	Mexico	CL&MX	Hiroshima	2	Japan	JP&KR
Monterrey	4	Mexico	CL&MX	Takamatsu	2	Japan	JP&KR
Torreón	3	Mexico	CL&MX	Wakayama	1	Japan	JP&KR
Saltillo	2	Mexico	CL&MX	Tokushima	1	Japan	JP&KR
Culiacán	1	Mexico	CL&MX	Kitakyushu	1	Japan	JP&KR
Durango	2	Mexico	CL&MX	Matsuyama	2	Japan	JP&KR
Tampico	1	Mexico	CL&MX	Fukuoka	2	Japan	JP&KR
San Luis Potosí	3	Mexico	CL&MX	Kochi	4	Japan	JP&KR
Aguascalientes	3	Mexico	CL&MX	Oita	1	Japan	JP&KR
Benito Juárez	3	Mexico	CL&MX	Kumamoto	2	Japan	JP&KR
León	2	Mexico	CL&MX	Nagasaki	2	Japan	JP&KR
Mérida	3	Mexico	CL&MX	Kagoshima	2	Japan	JP&KR
Guadalajara	2	Mexico	CL&MX	Naha	1	Japan	JP&KR
Irapuato	2	Mexico	CL&MX	Seoul Incheon	2	Korea	JP&KR
Querétaro	4	Mexico	CL&MX	Cheongju	4	Korea	JP&KR
Celaya	3	Mexico	CL&MX	Daejeon	2	Korea	JP&KR
Pachuca de Soto	3	Mexico	CL&MX	Pohang	2	Korea	JP&KR
Morelia	3	Mexico	CL&MX	Daegu	2	Korea	JP&KR
Mexico City	3	Mexico	CL&MX	Jeonju	2	Korea	JP&KR
Xalapa	3	Mexico	CL&MX	Ulsan	1	Korea	JP&KR
Toluca	3	Mexico	CL&MX	Busan	2	Korea	JP&KR
Veracruz	3	Mexico	CL&MX	Changwon	1	Korea	JP&KR
Puebla	3	Mexico	CL&MX	Gwangju	2	Korea	JP&KR
Cuernavaca	2	Mexico	CL&MX				
Centro	3	Mexico	CL&MX				
Oaxaca de Juárez	3	Mexico	CL&MX				
Acapulco de Juárez	3	Mexico	CL&MX				
Tuxtla Gutiérrez	3	Mexico	CL&MX				

Appendix 1-2. Metropolitan area names in Europe region (EU)

Metropolitan area name	Cluster	Country	Metropolitan area name	Cluster	Country
Vienna	4	Austria	Brussels	2	Belgium
Graz	4	Austria	Antwerp	2	Belgium
Linz	2	Austria	Ghent	1	Belgium
Prague	4	Czech Republic	Liege	4	Belgium
Brno	2	Czech Republic	Athens	3	Greece
Ostrava	2	Czech Republic	Thessalonica	2	Greece
Berlin	4	Germany	Budapest	4	Hungary
Hamburg	2	Germany	Dublin	4	Ireland
Munich	4	Germany	Rome	4	Italy
Cologne	1	Germany	Milan	3	Italy
Frankfurt	4	Germany	Naples	3	Italy
Essen	2	Germany	Turin	3	Italy
Stuttgart	4	Germany	Palermo	3	Italy
Leipzig	1	Germany	Genova	1	Italy
Dresden	4	Germany	Florence	3	Italy
Dortmund	1	Germany	Bari	3	Italy
Düsseldorf	1	Germany	Bologna	4	Italy
Bremen	1	Germany	Catania	2	Italy
Hanover	4	Germany	Venice	1	Italy
Nuremberg	2	Germany	The Hague	2	The Netherlands
Bochum	1	Germany	Amsterdam	4	The Netherlands
Freiburg im Breisgau	2	Germany	Rotterdam	4	The Netherlands
Augsburg	2	Germany	Utrecht	4	The Netherlands
Bonn	4	Germany	Eindhoven	2	The Netherlands
Karlsruhe	4	Germany	Warsaw	4	Poland
Saarbrücken	1	Germany	Lódz	1	Poland
Duisburg	4	Germany	Kraków	4	Poland
Mannheim	4	Germany	Wroclaw	4	Poland
Münster	2	Germany	Poznan	4	Poland
Aachen	1	Germany	Gdansk	4	Poland
Tallinn	1	Estonia	Lublin	2	Poland
Madrid	3	Spain	Katowice	1	Poland
Barcelona	3	Spain	Lisbon	4	Portugal
Valencia	2	Spain	Porto	4	Portugal
Seville	2	Spain	Stockholm	2	Sweden
Zaragoza	4	Spain	Gothenburg	3	Sweden
Málaga	2	Spain	Malmö	3	Sweden
Las Palmas	3	Spain	Ljubljana	4	Slovenia
Bilbao	4	Spain	Bratislava	2	Slovak Republic
Helsinki	2	Finland	London	2	United Kingdom
Paris	2	France	Birmingham (UK)	3	United Kingdom
Lyon	2	France	Leeds	1	United Kingdom
Toulouse	2	France	Bradford	2	United Kingdom
Strasbourg	2	France	Liverpool	2	United Kingdom
Bordeaux	2	France	Manchester	3	United Kingdom
Nantes	2	France	Cardiff	3	United Kingdom
Lille	2	France	Sheffield	2	United Kingdom
Montpellier	2	France	Bristol	4	United Kingdom
Saint-Étienne	2	France	Newcastle	4	United Kingdom
Rennes	2	France	Leicester	1	United Kingdom
Grenoble	2	France	Portsmouth	2	United Kingdom
Toulon	2	France	Nottingham	1	United Kingdom
Marseille	4	France	Glasgow	2	United Kingdom
Nice	2	France	Edinburgh	1	United Kingdom
Rouen	1	France			

Appendix 1-3. Metropolitan area names in United States (US)

Metropolitan area name	Cluster	Metropolitan area name	Cluster
Seattle	2	Wichita	3
Portland	3	Richmond	3
Minneapolis	4	Norfolk-Portsmouth-Chesapeake-Virginia Beach	4
Milwaukee	3	Fresno	3
Madison	1	Las Vegas	4
Buffalo	4	Nashville	4
Grand Rapids	3	Tulsa	1
Albany	3	Raleigh	3
Detroit	3	Oklahoma City	3
Boston	3	Charlotte	3
Chicago	4	Albuquerque	2
Providence	3	Memphis	4
Toledo	4	Little Rock	3
Cleveland	3	Los Angeles	2
Des Moines	3	Columbia	1
Omaha	1	Atlanta	4
Akron	2	Phoenix	4
New York	3	Birmingham	1
Salt Lake City	2	Dallas	3
Pittsburgh	3	San Diego	3
Harrisburg	1	Fort Worth	3
Philadelphia	3	Charleston	1
Columbus	3	Tucson	3
Denver	4	El Paso	4
Indianapolis	3	Baton Rouge	4
Dayton	3	Austin	4
Baltimore	2	Jacksonville	1
Cincinnati	1	New Orleans	4
Washington	4	Houston	4
Kansas City	1	San Antonio	1
Colorado Springs	1	Orlando	4
Saint Louis	4	Clearwater/Saint Petersburg	4
Sacramento/Roseville	3	Tampa	1
Louisville	1	Miami	2
San Francisco	3	Mcallen	1

Appendix 2. Results of determinants analysis (Dependent variable is CO_2/POP)

VARIABLES	All sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4
AU&CA×DENS	-0.0472***	-0.545***	0.00353***	N.A.	1.011***
AU&CA×COMM	-0.478***	-2.122***	0.0552***	N.A.	-11.72***
AU&CA×CORE	-0.0238	3.484***	0.128*	N.A.	13.23***
CL&MX×DENS	0.000141***	0.00331***	0.000522***	0.000544***	-0.00816*
CL&MX×COMM	0.0125***	0.219***	0.00270	-0.0123***	0.706***
CL&MX×CORE	-0.00803*	0.371***	-0.0660	-0.0718***	-0.386***
EU×DENS	-0.00151	-0.00435	0.00207***	0.000393**	0.00315
EU×COMM	-0.122**	-0.244**	0.0302	0.00162	-0.0980
EU×CORE	-0.0359	-0.129	0.0177	0.0377	0.0782
JP&KR×DENS	0.000600	-0.00383***	0.000128***	N.A.	-0.00164***
JP&KR×COMM	-0.0966	-0.174***	0.0129***	N.A.	-0.0363***
JP&KR×CORE	-0.158**	-0.0989***	0.0106	N.A.	0.0995***
US×DENS	-0.000517***	0.0270***	0.00567***	0.00511***	-0.0169***
US×COMM	0.0290***	0.235***	0.0331***	-0.00855***	-0.0845***
US×CORE	0.0289***	0.105***	0.198***	0.0152***	-0.0599***
2005 year dummy	-0.0976	0.327	-0.202**	-0.383	-0.224
2008 year dummy	-0.636	-0.455	-0.526***	-0.919	-1.020
Constant	63.34**	-34.92***	-7.607	1.348	-0.0841
Observations	828	162	291	180	195
R-squared	0.292	0.640	0.737	0.474	0.512

Note 1: *denotes significance at 10% level, **denotes significance at 5% level, ***denotes significance at 1% level.

Note 2: " N.A." indicates that there is no sample selected, as in cluster 3 in the AU&CA and JP&KR region groups.

Appendix 3. Results of determinants analysis (Dependent variable is GDP/POP)

VARIABLES	All sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4
AU&CA×DENS	-32.60***	-1,419***	-18.46***	N.A.	972.1
AU&CA×COMM	1.845	-19,296***	122.6	N.A.	-9,538
AU&CA×CORE	257.9	-29,108***	324.5	N.A.	10,746
CL&MX×DENS	0.151***	-9.544***	1.078***	0.975***	-23.86***
CL&MX×COMM	40.70***	27.67***	66.62***	-38.20***	580.7**
CL&MX×CORE	220.1***	-39.18***	608.5***	63.46***	40.83
EU×DENS	5.451**	6.478	10.09***	-2.126	8.181
EU×COMM	325.2***	219.2*	598.9***	-57.29	468.6**
EU×CORE	121.9	-25.73	446.8***	-88.73	-108.9
JP&KR×DENS	-0.938	-5.705**	-0.915	N.A.	3.137***
JP&KR×COMM	-89.77**	-106.7	-92.26***	N.A.	25.99***
JP&KR×CORE	-40.60	26.66	-144.4	N.A.	85.98***
US×DENS	18.46***	65.21***	-28.75***	18.28***	-4.629***
US×COMM	70.45***	292.1***	-63.60***	37.35***	-33.35***
US×CORE	-100.8***	104.4***	340.9***	-277.7***	-189.8***
2005 year dummy	2,899***	2,727***	2,912***	2,365**	3,276***
2008 year dummy	4,224***	3,844***	4,552***	3,096***	4,726***
Constant	25,986	17,920***	7,448	53,151	8,911***
Observations	828	162	291	180	195
R-squared	0.746	0.797	0.844	0.852	0.744

Note 1: *denotes significance at 10% level, **denotes significance at 5% level, ***denotes significance at 1% level.

Note 2: "N.A." indicates that there is no sample selected, as in cluster 3 in the AU&CA and JP&KR region groups.

Appendix 4. Results summary of determinants analysis of driving factors

		DENS			COMM			CORE		
		CO_2/GDP	GDP/POP	CO_2/POP	CO_2/GDP	GDP/POP	CO_2/POP	CO_2/GDP	GDP/POP	CO_2/POP
AU&CA	All	−***	−***	−***	−***		−***			
	C1		−***	−***	+***	−***	−***	+***	−***	+***
	C2	+***	−***	+***			+***			+*
	C3	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
	C4	+***		+***	−***		−***	+***		+***
CL&MX	All	+***	+***	+***	+*	+***	+***	−***	+***	−*
	C1	+***	−***	+***	+***	+***	+***	+***	−***	+***
	C2	+***	+***	+***		+***		−*	+***	
	C3	+***	+***	+***	−***	−***	−***	−***	+***	−***
	C4		−***	−*		+**	+***			−***
EU	All	−*	+**		−***	+***	−**	−*		
	C1	−***			−***	+*	−**			
	C2		+***	+***	−***	+***			+***	
	C3		+***							
	C4					+**		+***		
JP&KR	All	+***					−**	−**		−**
	C1		−**	−***	−*		−***			−***
	C2			+***	+**	−***	+***			
	C3	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
	C4	−***	+***	−***	−***	+***	−***	+***	+***	+***
US	All	−***	+***	−***	−***	+***	+***	+***	−***	+***
	C1	−***	+***	+***	+***	+***	+***	+***	+***	+***
	C2	+***	−***	+***	+***	−***	+***	+***	+***	+***
	C3	−***	+***	+***	−***	+***	−***	+***	−***	+***
	C4	−***	−***	−***	−***	−***	−***	+***	−***	−***

Note 1: *denotes significance at 10% level, **denotes significance at 5% level, ***denotes significance at 1% level.

Note 2: "+" indicates that the sign of the coefficient score is positive; "−" indicates that the sign of the coefficient score is negative.

Note 3: "N.A." indicates that there is no sample selected, as in cluster 3 in the AU&CA and JP&KR region groups.