Spatial Decomposition of Drivers to Regional Traffic Flow in Philippine Cities using LMDI

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One of the ways to apply circular economy thinking in transportation is to transition from a product-based to a service-based model, i.e. reducing private vehicle ownership and use. This is somehow reflected in recent developments: from ridesharing, bike-sharing to car-sharing services in various countries. However, studies show that private vehicle ownership will continue to outgrow public transport use in developing countries up to the next decade as income levels rise. Recent vehicle ownership statistics in the Philippines support this. In this study, spatial decomposition methodology is used to compare the drivers to increasing traffic flow in different regions of the Philippines. The effects of potential explanatory factors including population, economic activity, travel intensity and modal structure to regional differences in traffic flow are estimated. Interestingly, results show that high traffic flow is only either driven by high economic activity, or high travel intensity – never both at the same time. High economic activity regions also tend to have low travel intensity, and vice versa. Insights can be drawn from the results to formulate policy recommendations for controlling increasing traffic flow.

1. Introduction

The Philippines is an archipelagic country composed of three main island groups – Luzon, Visayas and Mindanao. 47.5 % of the population is urban, based on Worldometers (2020) estimates. The country is divided into 17 regions within the three island groups of Luzon (Regions 1 to 5, Cordillera Administrative Region [CAR] and National Capital Region [NCR]), Visayas (Regions 6 to 8) and Mindanao (Regions 9 to 13 and Autonomous Region in Muslim Mindanao [ARMM] and Caraga Administrative Region [CARAGA]). Rapal et al. (2017) highlighted regional socio-economic differences in the Philippines, using a multicriteria analysis study. NCR is also known as the national capital Metro Manila – a megacity housing over $12E^{+6}$ residents. There are 122 cities in the Philippines, of which thirty-three (33) are classified as "highly urbanized" and five (5) as "independent component", the rest are component cities of the provinces in which they are geographically located.
A 2019 report detailing the traffic situation in 416 cities in 57 countries noted that Metro Manila traffic has the second worst traffic in the world with drivers expecting to spend an average of 71 % additional travel time stuck in traffic (Esguerra, 2020). In the context of rising travel demand and private vehicle use, Dangay and Gately (1999) investigated income's effect on worldwide car ownership using the Gompertz function and concluded that there exists a strong historical relationship between the growth of per-capita income and the growth of the number of vehicles per capita. From recent developments in transport, Martin et al. (2010) showed that carsharing can reduce private vehicle use for non-work trips. Also, Ubando et al. (2019) showed how electric vehicle use can be optimized for minimal carbon emissions. Recent studies show the use of logarithmic mean Divisia index (LMDI) to analyze transport sector issues as seen in Papagiannaki and Diakoulaki (2009), focusing on the differences in the transportation profiles; Wang et al. (2011), introducing the avoid, shift and improve strategies; Ding et al. (2013), developing scenarios for analysis; and Guo et al. (2014), identifying the drivers of CO_2 emissions. This indicates that LMDI is used reliably to analyze transportation problems.

In Lopez et al. (2018), the authors analyzed the drivers to CO_2 emissions from the Philippine transportation sector using the LMDI. The results showed that the primary driving factor is increased energy intensity, which the authors related to increasing private transport use. Based on vehicle registration data, this increase is mostly occurring in the provinces outside the nation's capital of Metro Manila. In this present study, the authors dig deeper into this problem by uncovering the characteristics of low and high traffic regions in the Philippines through the application of spatial LMDI decomposition analysis.

Ang et al. (1998) introduced the LMDI method. Two main approaches utilized in decomposition analysis are: Lapeyres- and Divisia-related (Ang, 2004). The LMDI method is preferred over other common methods due to its perfect decomposition and ability to handle cases with zero values. LMDI has been shown to be multidisciplinary, such as in Lopez et al. (2017), analyzing the effects of electricity trading to carbon emissions mitigation.

In recent literature, Ang et al. (2015) introduced a novel approach for spatial decomposition using a case study on energy consumption. The method provides a simple and elegant manner to compare and benchmark various indices among cities, regions, or countries using LMDI, or a similar decomposition analysis technique. Similarly, Zhang et al. (2019) applied temporal and spatial decomposition analysis modeling to identify the driving forces to CO_2 emissions of China's transport sector. From the spatial perspective, the income effect, energy intensity effect, and transportation structure effect were the key influencing factors that enlarged the gap of CO_2 emissions from various transport sectors in the key study areas. Chen and Yang (2015) applied LMDI-coupled decomposition analysis to decompose the driving factors of CO_2 emissions in eight sub-periods over 1995 to 2011.

In this study, spatial decomposition methodology will be used to analyze increasing traffic flow in different regions of the Philippines. To the knowledge of the authors, this is the first time a spatial decomposition study will be performed to analyze drivers to traffic flow. The results can provide a tool for researchers to identify underlying factors which can help manage increasing travel demand in cities. The effects of potential explanatory factors are compared for each region.

2. Methods and Data

Data is extracted from the Philippine Statistics Authority (2015). Spatial decomposition analysis based on Ang et al. (2015) is used in this study to understand the characteristics of high- and low- traffic regions across the Philippines. Traffic flow in this study is defined as total vehicle-kilometers (*Vkm*) for a given year. Four factors, with regards to how they affect traffic flow in each region will be investigated: population (*pop*), economic activity (*act*), travel intensity (*int*), and modal structure (*str*).

The population effect (ΔVKM_{pop}) quantifies the difference in traffic flow between regions due to population differences. The economic activity effect (ΔVKM_{act}) is due to the difference in gross domestic product per capita (GDP per capita). The travel intensity effect (ΔVKM_{int}) is due to the difference in vehicle-kilometers traveled per GDP (VKM/GDP). The modal structure effect (ΔVKM_{str}) is due to the difference in the share of vehicle-kilometers traveled per type of vehicle (VKM_i/VKM), where subscript *i* refers to vehicular mode *i* (e.g. taxi, bus, private car, etc).

To perform index decomposition analysis (IDA), the identity function on Eq(1) will be used.

$$\Delta VKM = \sum_i \left(pop \times \frac{GDP}{pop} \times \frac{VKM}{GDP} \times \frac{VKM_i}{VKM} \right) = \sum_i (pop \times act \times int \times str_i) \tag{1}$$

Typically, in decomposition analysis studies, the effects are estimated from a base year to a final year. The analysis is called temporal decomposition. When the effects are estimated between a certain region and another, the analysis becomes spatial decomposition. Ang et al. (2015) detailed the spatial decomposition analysis procedure using LMDI. In this process, the national average is calculated and every region is benchmarked against it. For those familiar with temporal decomposition, the national average takes the place of the base year. For policy makers who wish to know why differences exist among regions, the implications of these differences and the best course of action to be taken, this approach can be utilized to reduce the number of decomposition cases and at the same time avoid arbitrariness in choosing a benchmark reference.

The individual effects can be calculated using the logarithmic functions in Eq(2) to Eq(5) below. The logarithmic functions provide perfect decomposition, unlike other decomposition methods which generate unexplained residuals. More information on this methodology can be read in Ang (2015).

$$\Delta VKM_{pop} = \frac{VKM^R - VKM^\mu}{lnln\,VKM^R - lnln\,VKM^\mu}\, ln\,ln\left(\frac{pop^R}{pop^\mu}\right) \tag{2}$$

$$\Delta VKM_{act} = \frac{VKM^R - VKM^\mu}{lnln\,VKM^R - lnln\,VKM^\mu}\, ln\,ln\left(\frac{act^R}{act^\mu}\right) \tag{3}$$

$$\Delta VKM_{int} = \frac{VKM^R - VKM^\mu}{lnln\ VKM^R - lnln\ VKM^\mu} ln\ ln\left(\frac{int^R}{int^\mu}\right) \tag{4}$$

$$\Delta VKM_{str} = \sum_i \frac{VKM_i^R - VKM_i^\mu}{lnln\ VKM_i^R - lnln\ VKM_i^\mu} lnln\left(\frac{str_i^R}{str^\mu}\right) \tag{5}$$

The superscripts *R* and *μ* refer to region *R* and the national average *μ*. If it is desired to compare two specific regions, e.g. region 1 and region 2, this is done using Eq(6).

$$\Delta VKM_j^{(R1-R2)} = \Delta VKM_j^{(R1-\mu)} - \Delta VKM_j^{(R2-\mu)} \tag{6}$$

where ΔVKM_j is the difference in traffic flow due to effect *j*; subscript *j* refers to effect *j* (e.g. *pop*, *act*, *int*, or *str*); the superscript *(R1 – μ)* refers to the estimate of effect *j* between region 1 and the national average, *μ*; the superscript *(R2 – μ)* refers to the estimate of effect *j* between region 2 and the national average, *μ*; and the superscript *(R1 – R2)* refers to the estimate of effect *j* between region 1 and region 2.

3. Results and discussions

3.1 Key statistics

Key regional statistics are shown in Figures 1a and 1b. Regions 3, 4A and NCR greatly outweigh other regions in terms of population and GDP. This is because NCR is the national capital and economic center of the country, and it can be said that regions 3 and 4A are extensions of the capital. Geographically, regions 3 and 4A are bordering NCR to the north and south. All other regions are well-below the national average except for regions 6 and 7 in the Visayas area. As such, the same regions also dominate in terms of annual vehicle-kilometers traveled. Private gasoline-powered vehicles dominate modal share in almost all regions, except for NCR and CAR which are led by diesel-powered private vehicles (see Figure 2).
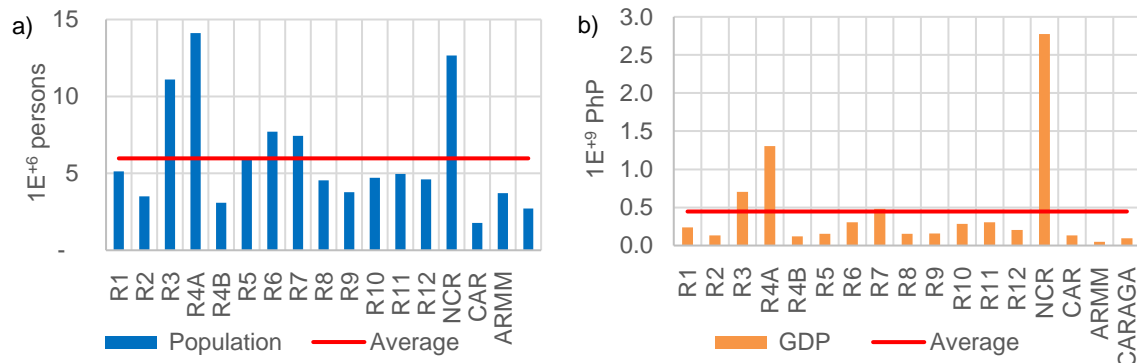

Figure 1: (a) Population by region in 2015; (b) GDP by region in 2015 (Philippine Statistics Authority, 2016)
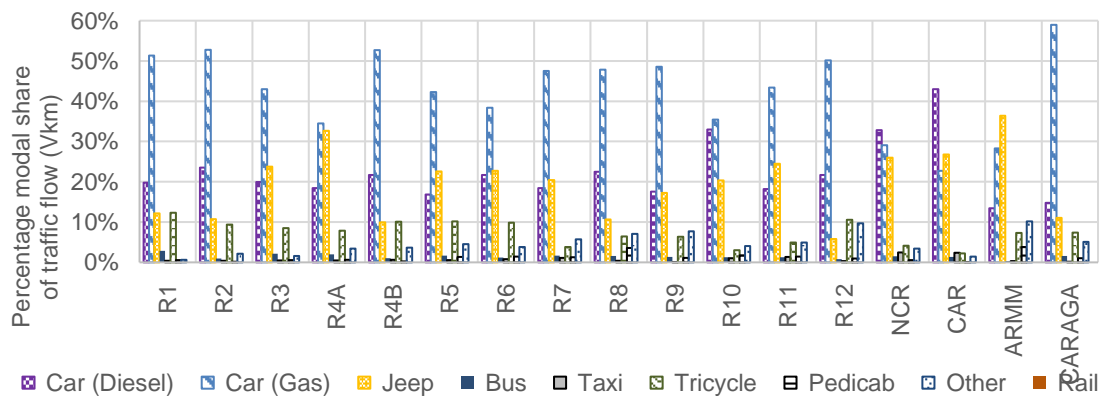

Figure 2: Modal share of regional traffic flow in vehicle-kilometers travelled per year by region. [Source: modelled using FIES 2015 data (PSA, 2015)]

3.2 Drivers

The variation in traffic flow between regions is mostly because of differences in population, travel intensity, and economic activity (see Figure 3). Interestingly, population growth is the main driving force to traffic flow in many cities, except for regions 5, 6, 8, NCR and ARMM. Regarding modal share, regional differences in jeepney and gasoline private car usage can also contribute significantly.
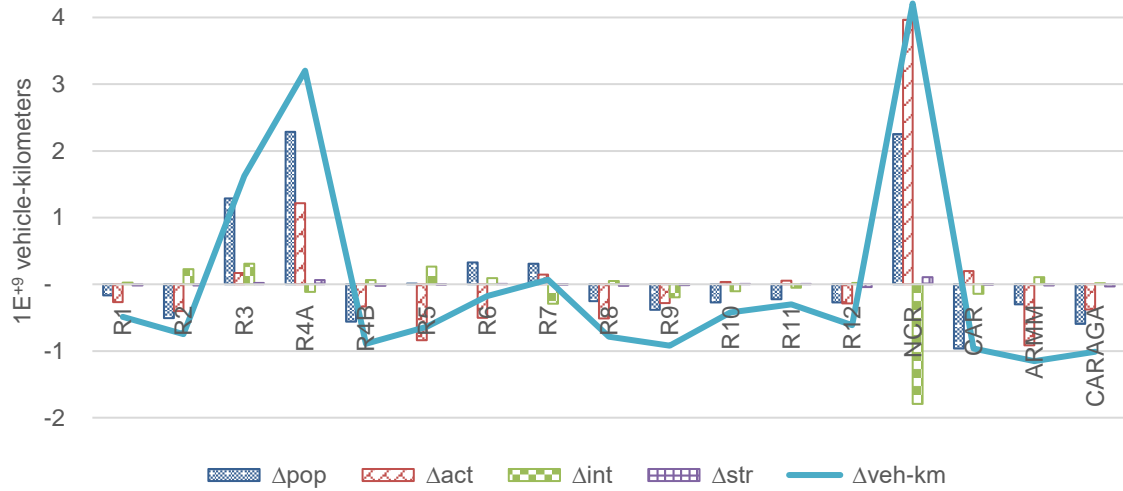

Figure 3: Effect estimates by region, as compared with the national average, μ

Regions which had relatively higher traffic flows had both high economic activity and high population. A possible interpretation for this is that these places attract large populations because of the career and financial opportunities they offer. For context, the major cities in these regions are Metro Manila, Cebu, Angeles, Imus, and Sta. Rosa. This demand to be in the city then translates to high travel demand. Hickman et al. (2018) sheds more light on drivers to increasing private vehicle dependence in Metro Manila, emphasizing on the security and comfort aspect of it. On the other hand, most of the rest of the regions show below-average economic activities and populations, resulting to below-average traffic flows as well.
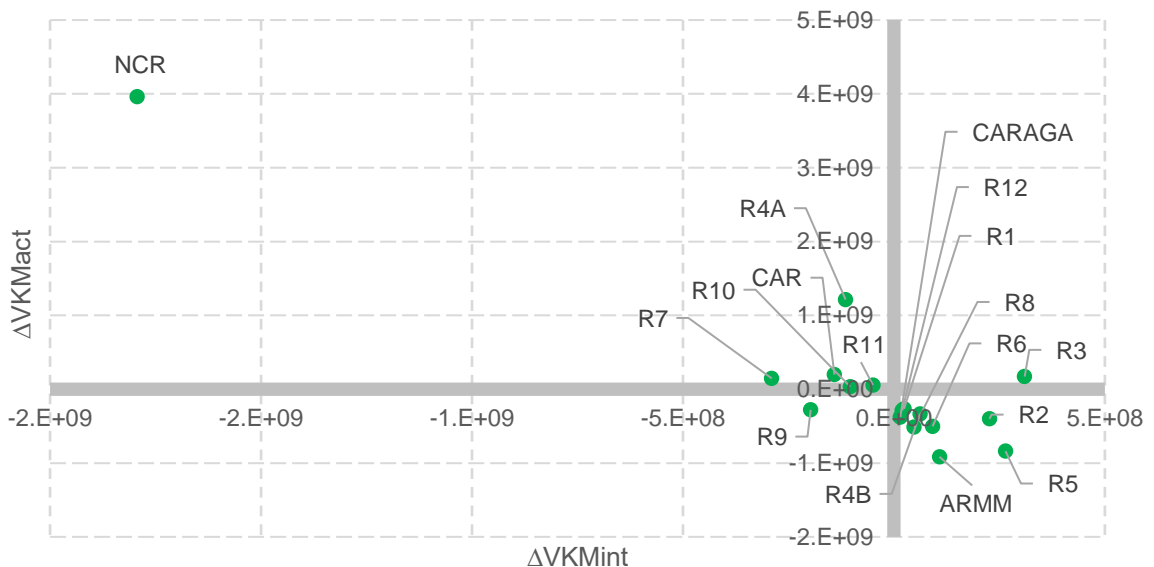

Figure 4: Activity and intensity effects polar plot for regions

In Figure 4, it can be seen that most regions occupy quadrants 2 and 4. This means that regions either had high economic activity or high travel intensity – never both at the same time. This is very interesting and potentially

points out an inequality issue which funnels most infrastructure investments to the affluent regions, while the developing regions barely receive any infrastructure development projects (e.g. light rail and other mass transport projects). As a result, the less affluent regions have to rely on private transport which are inefficient. Region 3 and 9 were exceptions to this. Region 3 both had high economic activity and high travel intensity, which suggests that economic growth in the region can result to unsustainable transport demand in the future if these two are not successfully decoupled.

In Figure 5, regions with above-average private gasoline car modal share occupy quadrants 1 and 4, while those with above-average jeepney modal share occupy quadrants 1 and 2. Similar to Figure 4, the regions also mostly only occupy quadrants 2 and 4, meaning traffic flow in the regions either have above-average jeepney modal share, or above-average private gasoline car modal share – never both as the same time. This suggests that the jeepney and private gasoline car models are the ones which are traded-off the most when traffic flows increase or decrease. It has to be noted though from Figure 3 that modal structure effects only contribute minimal effects on the total traffic flow.
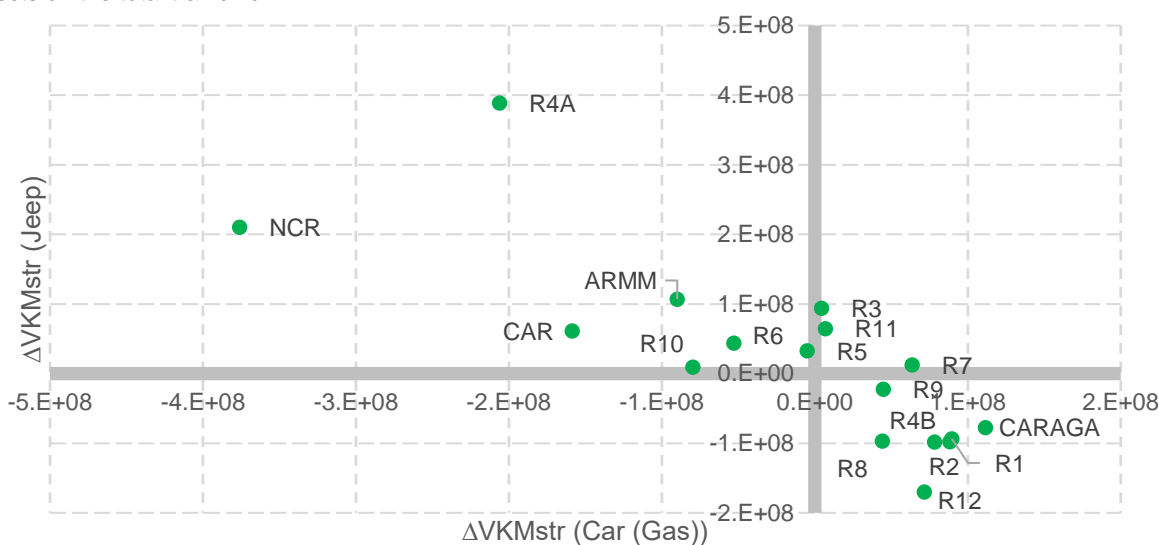

Figure 5: Polar plot of effects of regional differences in jeepney and private car modal share.

4. Conclusion

In this brief paper, the authors demonstrated how spatial decomposition analysis can be used to compare driving factors to high-traffic flow among regions. To the knowledge of the authors, this is the first study to do this. By doing this, insights can be obtained on why certain cities / regions have higher relative traffic flow than others. The results can be further developed to guide policy making for transportation infrastructure planning.

The overall results were unsurprising – differences in population, travel intensity and economic activity mainly drive the relative differences in traffic flow. However, the details were what made the study interesting. For example, it has been found that the regional traffic flows are mostly only either driven by high economic activity, or high travel intensity – never both at the same time. High economic activity regions tend to have low travel intensity, and vice versa. More so, jeepney trips are traded-off for private gasoline car trips in regions with high traffic flow.

In an extended study, the findings can be further validated using data on land area, total length of roads and highways within regions, employment rates. Policy implications may also then be recommended.

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