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Association between vehicular emissions and cardiorespiratory disease risk in Brazil and its variation by spatial clustering of socio-economic factors

Weeberb J. Requia [a,*], Petros Koutrakis [b], Henrique L. Roig [c], Matthew D. Adams [a], Cleide M. Santos [d]

[a] McMaster University, 1280 Main Street West, Hamilton, Ontario L8S 4K1, Canada
[b] Harvard University, United States
[c] University of Brasilia, Brazil
[d] Brazilian Health Foundation, Brazil

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ABSTRACT

Many studies have suggested that socio-economic factors are strong modifiers of human vulnerability to air pollution effects. Most of these studies were performed in developed countries, specifically in the US and Europe. Only a few studies have been performed in developing countries, and analyzed small regions (city level) with no spatial disaggregation. The aim of this study was to assess the association between vehicle emissions and cardiorespiratory disease risk in Brazil and its modification by spatial clustering of socio-economic conditions. We used a quantile regression model to estimate the risk and a geostatistical approach (K means) to execute spatial cluster analysis. We performed the risk analysis in three stages. First, we analyzed the entire study area (primary analysis), and then we conducted a spatial cluster analysis based on various municipal-level socio-economic factors, followed by a sensitivity analysis. We studied 5444 municipalities in Brazil between 2008 and 2012. Our findings showed a significant association between cardiorespiratory disease risk and vehicular emissions. We found that a 15% increase in air pollution is associated with a 6% increase in hospital admissions rates. The results from the spatial cluster analysis revealed two groups of municipalities with distinct sets of socio-economic factors and risk levels of cardiorespiratory disease related to exposure to vehicular emissions. For example, for vehicle emissions of PM in 2008, we found a relative risk of 4.18 (95% CI: 3.66, 4.93) in the primary analysis; in Group 1, the risk was 0.98 (95% CI: 0.10, 2.05) while in Group 2, the risk was 5.56 (95% CI: 4.46, 6.25). The risk in Group 2 was 480% higher than the risk in Group 1, and 35% higher than the risk in the primary analysis. Group 1 had higher values (3rd quartile) for urbanization rate, highway density, and GDP; very high values ($\geq$ 3rd quartile) for population density; median values for distance from the capital; and lower values (1st quartile) for rural population density. Group 2 had lower values (1st quartile) urbanization rate; median values for highway density, GDP, and population density; between median and third quartile values for distance from the capital; and higher values (3rd quartile) for rural population density. Our findings suggest that socio-economic factors are important modifiers of the human risk of cardiorespiratory disease due to exposure to vehicle emissions in Brazil. Our study provides support for creating effective public policies related to environmental health that are targeted to high-risk populations.

1. Introduction

Cardiorespiratory diseases are a serious public health problem worldwide. According to the World Health Organization (WHO, 2014a), cardiovascular and respiratory diseases were responsible for 17.5 and 4 million global death in 2012, respectively. Air pollution is considered to be one of the main contributors to cardiorespiratory diseases (Cohen et al., 2005; Fajersztajn et al., 2013). In 2010, 3 million deaths worldwide were caused by air pollution (Lim et al., 2012). Two years later, this number increased to 7 million (WHO, 2014b). Particulate matter ($PM_{2.5}$) specifically contributes to approximately 2 million premature deaths per year, making it as the 13th leading cause of mortality worldwide

* Corresponding author.
E-mail addresses: weeberb@gmail.com, requiajw@mcmaster.ca (W.J. Requia), petros@hsph.harvard.edu (P. Koutrakis), roig@unb.br (H.L. Roig), adamsmd@mcmaster.ca (M.D. Adams), cleidemouras@gmail.com (C.M. Santos).

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(Lozano et al., 2012).

Among air pollution sources, vehicle emissions are of particular concern (Lipfert and Wyzga, 2008; Gallardo et al., 2012; Réquia Júnior et al., 2015a). Motor vehicle emissions are responsible for 30% of nitrogen oxides (NO_x), 14% of carbon dioxide (CO_2), 54% of carbon monoxide (CO), and 47% of non-methane hydrocarbon (NMHC) in global emissions (Sokhi, 2011). Several studies have shown that traffic-related air pollution is associated with health effects, such as cardiorespiratory diseases (Mortimer et al., 2012; Réquia Júnior et al., 2015b), premature mortality (Lin et al., 2004; Lelieveld et al., 2015), diabetes (Nicole, 2015), and nervous system diseases (Genc et al., 2012). According to Jacobson (2007), both gasoline and ethanol combustion are anticipated to cause at least 10,000 premature deaths in the United States in 2020.

Many studies have demonstrated the spatial heterogeneity of human exposure to air pollution (Tian et al., 2010; Khedairia and Khadir, 2012; Austin et al., 2013; Zou et al., 2014; Carreras et al., 2015; Réquia Júnior and Roig, 2015). Socio-economic factors are considered to be strong modifiers of human vulnerability to air pollution effects. Most of these studies were performed in developed countries, especially in the US and in Europe. Only a few studies on the influence of socio-economic factors on the health risks of air pollution have been performed in developing countries, and they analyzed only small regions (at the city level) with no spatial disaggregation (Troncoso and Cifuentes, 2012; Miranda et al., 2014; Carreras et al., 2015).

Overall, developing countries have specific conditions that alter the association between air pollution and human health (Carreras et al., 2015). These include a higher rate of urban growth, low income, social inequality, and inefficient regulation and control of air pollution sources (D'angiola et al., 2010; Silva et al., 2012; Réquia Júnior et al., 2015b). Air pollution exposure is not tracked as well in certain countries. For example, in terms of air pollution control, Brazil, Argentina, Peru, Colombia, and Mexico have 1.3, 0.24, 0.23, 0.26, and 0.35 stations per one-million inhabitants, respectively (Alves et al., 2014). In contrast, the USA has 16 stations (Alves et al., 2014), Japan has 15 stations (Fukushima, 2006), and Germany has 23 stations (UBA, 2013) stations per one-million inhabitants.

A better understanding of the spatial variation in human exposure to air pollution under various socio-economic conditions in developed and developing countries can reveal the associated risks to health and guide more effective public policies for urban planning, environmental health, and economic development (Fan et al., 2012; Santos-Juusela et al., 2013; Réquia Júnior and Roig, 2015). The aim of this study was to evaluate the association between vehicle emissions and cardiorespiratory disease risk in Brazil and its modification by municipal-level variations in socio-economic conditions.

2. Materials and methods

2.1. Study design and data

We conducted a cross-sectional analysis of the association between vehicle emissions and hospital admissions for cardiorespiratory diseases in Brazil. The study included data for the entire country of Brazil, which has 200 million inhabitants and an area of 8,515,767 km^2 divided into 26 states and a Federal District. These are further divided into 5570 municipalities, which are the smallest regions recognized by the Brazilian political system. The study was performed in three stages: i) statistical analysis – primary analysis; ii) cluster analysis; and iii) statistical analysis – sensitivity analysis (Fig. 1).

Health data collected from the National Health Database

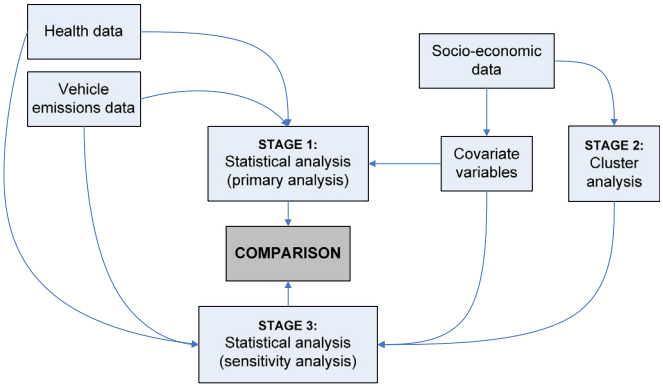

Fig. 1. Stages of the research analysis.

(DATASUS, 2013) included the number of annual hospital admissions for circulatory (ICD-10, I00-I99) and respiratory (ICD-10, J00-J99) diseases between 2008 and 2012 for each Brazilian municipality. We used information from the national census provided by the Brazilian Institute of Geography and Statistics (IBGE, 2012) to calculate the rate of hospital admissions (admissions per 1000 people).

Vehicle emissions data were estimated by our research group in a previous analysis. We predicted the vehicular emissions (tons per year) using a bottom-up method within each of the 5570 municipalities in Brazil from 2001 to 2012 for CO, NMHC, methane (CH_4), NO_x, and PM. For PM emissions, we considered the sum of emissions from exhaust, brakes, tires, and pavement wear. We used the following equation to estimate emissions:

$$E_{x,\,i,\,z,\,y} = \frac{\left[\left(Vf_{x,i,y} \times \alpha_y\right) \times Dt_y \times Ef_{i,z,y}\right]}{10^6} \quad (1)$$

where: *E* are the annual emissions in metric tons; *Vf* is the number of vehicles; α is fraction of fleet in use; *Dt* is the average distance traveled in km/year; *Ef* is the emission factor in grams of pollutant per unit distance – (g/km); *x* is the municipal district (5570); *i* is the year considered to estimate emissions (from 2001 to 2012); *z* is the pollutant type, and; *y,* is the vehicle type.

We considered six vehicle categories: light vehicles (passenger cars), utility vehicles (for transport of passengers or goods), motorcycles, trucks (light, middle, and heavy duty), urban buses, and interstate buses. Finally, to estimate the total emissions of a pollutant *z* for year *i*, and for municipal district *x*, we used the following equation:

$$TAE_{z,i,x} = E_{Lv,z,i,x} + E_{Uv,z,i,x} + E_{Mo,z,i,x} + E_{Tr,z,i,x} + E_{Ub,z,i,x} + E_{Ib,z,i,x} \quad (2)$$

where *TAE* are the emissions, in tons, for light vehicles, *Lv*, utility vehicles *Uv*, motorcycles, *Mo*, trucks, *Tr*, urban buses, *Ub*, and interstate buses, *Ib*. For the socio-economic data, we considered Gross Domestic Product (GDP), urbanization rate (% of urbanized area), highway density (length of highways, km, per municipality area, km^2), distance of municipality from the state's capital (km), total population density, and rural population density. Each socio-economic datum refers to the municipality level. Highway density and distance from the capital were calculated using GIS techniques. Other data were provided by IBGE (2012). We chose distance from the capital to represent socio-economic data because is a proxy indicator of health system quality. In Brazil, main hospitals tend to be located in capitals.

Missing socio-economic data occurred in 126 municipalities and these were removed from our study, which resulted in the analysis conducted in 5444 municipalities in Brazil (98%).

Spatial data generation and processing was done with ArcGIS,

version 10.3 (ESRI, 2013).

2.2. Statistical analysis – primary analysis

The purpose of the primary analysis was to evaluate the association between vehicle emissions and cardiorespiratory disease risk for the complete sample (5444 municipalities). We performed a statistical analysis using the quantile regression approach. This method assesses how the quantiles of the response variables change with the variation in the predictor variable (Koenker and Hallock, 2001; Koenker, 2005).

The response variable was the ratio of cardiorespiratory disease hospital admissions per 1000 inhabitants. We calculated the hospital admissions risk considering the effect from vehicle emissions (log of emissions) and using socio-economic data as covariate variable (GDP, urbanization rate, highway density, distance from the capital, population density, and rural population density). Eq. (3) describes the risk estimation.

$$Risk_{kij} = \beta_{kij} \times \left(75\text{th } Percentile_{kj} - 25\text{th } Percentile_{kj}\right) \quad (3)$$

where k is type of pollutant (CO, NMHC, CH_4, NO_x, and PM); i represents the quantile ith, which were 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, and 0.95; j is the year (2008–2012); β is the coefficient (slope) of the predictor variable (log of emissions); and *75*th *Percentile* – *25*th *Percentile* represents the interquartile range (a scaling factor of the predictor variable). We also inserted the covariate variables using the interquartile range.

We performed the statistical analysis using R software, version 2.10.1 using the package *quantreg* (Koenker, 2011).

2.3. Cluster analysis

We performed cluster analysis to identify groups of municipalities where socio-economic factors within each group are as similar as possible, and all the groups themselves are as different as possible. We used the geostatistical method k means, an approach that looks for the best solution that maximizes both within-group similarity and between group differences (Hartigan and Wong, 1979).

In the first step, the k mean algorithm identifies a seed feature randomly. Then all features are assigned to the closest seed feature. Finally, a mean data center is calculated for each group of features, and each feature is reassigned to the closest center. We configured the k mean algorithm to group features using the k nearest neighbors approach. This approach determines that a municipal district will only be included in a group if at least one other municipal district in the same group is a natural neighbor. The number of seed features selected randomly match the number of groups. To estimate the optimal number of groups, we applied the Calinski-Harabasz pseudo F-statistic, which is described by the following equations:

$$CH = \frac{\left(\frac{T^2}{nc-1}\right)}{\left(\frac{1-T^2}{n-nc}\right)} \quad (4)$$

where *CH* is the Calinski-Harabasz pseudo F-statistic; *nc* is the number of classes (groups); *n* is the number of features (municipal districts, which is equal to 5444); and T^2 is described as:

$$T^2 = \frac{SST - SSE}{SST} \quad (5)$$

where *SST* is a reflection of between-group differences (described by the Eq. (6)) and *SSE* is a reflection within-group similarity (described by the Eq. (7)).

$$SST = \sum_{m=1}^{nc}\sum_{j=1}^{ni}\sum_{k=1}^{nv}\left(V_{mj}^{k} - \bar{V}^{k}\right)^2 \quad (6)$$

$$SSE = \sum_{m=1}^{nc}\sum_{j=1}^{ni}\sum_{k=1}^{nv}\left(V_{mj}^{k} - \bar{V}_{g}^{k}\right)^2 \quad (7)$$

where *ni* is the number of features in group *m*; *nc* is the number of classes (groups); *nv* is the number of variables used to group features; V_{mj}^{k} is the value of the *k*th variable of the *j*th feature in the *m*th group; $\bar{V}^{k}$ is the mean value of the *k*th variable; and $\bar{V}_{g}^{k}$ is the mean value of the *k*th variable in group *m*.

We considered six variables to group features (nv): GDP, urbanization rate, highway density, distance from the capital, population density, and rural population density. We performed the cluster analysis using ArcGIS, version 10.3, using the tool *Mapping Clusters – Grouping Analysis*.

2.4. Sensitivity analysis (variation by spatial clustering of socio-economic factors)

We performed the sensitivity analysis to examine the robustness of the primary results based on the spatial clustering of socio-economic factors. To do so, we applied the same statistical method, as presented by Eq. (1), for each group of municipalities determined by the cluster analysis.

3. Results

3.1. Descriptive analysis

We evaluated hospital admissions for cardiorespiratory diseases in 5444 municipalities in Brazil (Appendix 1 – Summary Statistics for the Health Data.). The highest average number of hospital admissions per municipalities was in 2009, 487.35 ± 2077.11 (19 ± 11 considering the rate).

Fig. 2 shows the ratio of hospital admissions for cardiorespiratory diseases in each of the 5444 municipalities for each year of the analysis and a box plot chart showing the differences for the entire study period (2008–2012).

3.2. Spatio-temporal distribution of hospital admissions

Fig. 3 shows the spatio-temporal distribution of the cardiorespiratory disease hospital admissions rate, which decreased from 2008 to 2012. Overall, the municipalities with the higher hospital admissions rate were located in the Northeast, Midwest, and South. The municipalities with lower rates were located in the Northwest.

3.3. Spatial cluster analysis based on socio-economic factors

We performed a pseudo F-statistic test to estimate the optimum number of groups for analysis that maximizes both within-group similarity and between-group dissimilarity. We performed the test for 15 simulations (simulating 2 groups, 3 groups, 4 groups, …, 15 groups). We found the highest mean value of the pseudo F-statistic for two groups, value equal to 1590 (Appendix 2).

For the k mean analysis, an R^2 value was calculated for each variable. The R^2 indicates the variable that divides the study area into groups most effectively. Therefore, specifically for our analysis, the higher the R^2 value, the better the discrimination among

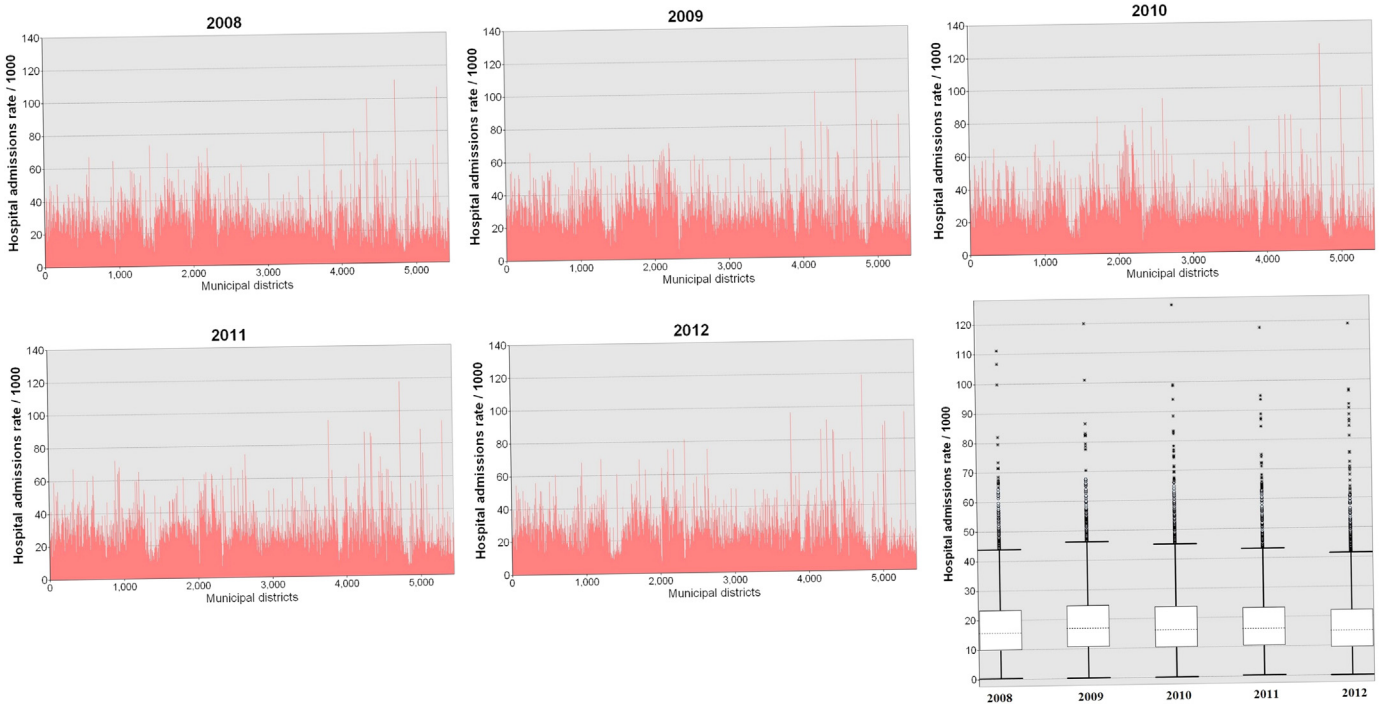

Fig. 2. Hospital admissions rate by municipality and box plot chart. Note: In the rate charts, the order for x-axis (municipal districts) was based on the ID of each spatial feature (polygon).

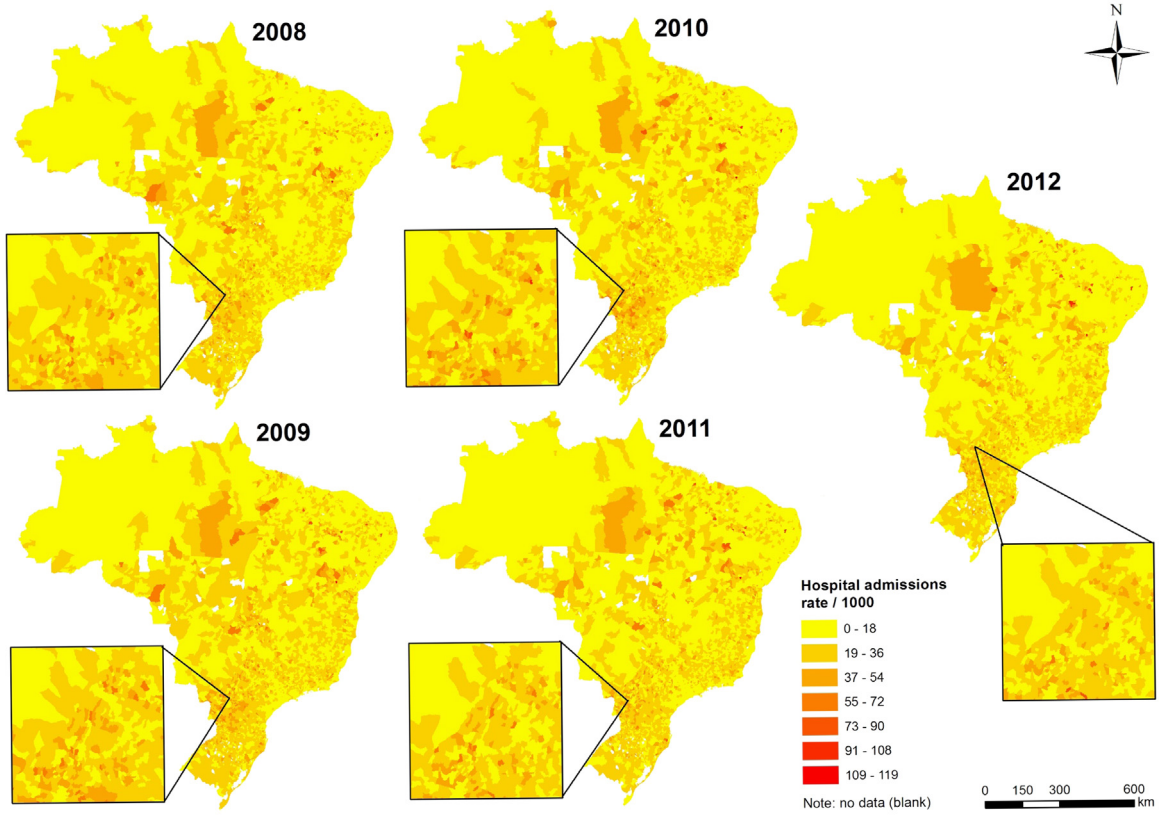

Fig. 3. Spatio-temporal distribution of hospital admissions in Brazil. Inset shows the same municipality in each year.

the municipal districts (R^2 value varies between 0 and 1). We found R^2 equal to 0.61 for rural population density; 0.57 for urbanization rate; 0.14 for highway density; 0.05 for GDP; 0.03 for population density; and 0.02 for distance from the capital.

Group 2 had a higher number of municipalities (2964) compared to Group 1 (2480). Fig. 4 shows the summary statistics (parallel box plot) for each socio-economic variable in each group. On average, Group 1 (blue) municipal districts had higher values (third quartile) for urbanization rate, highway density, and GDP; very high values ($\geq$ third quartile) for population density; median

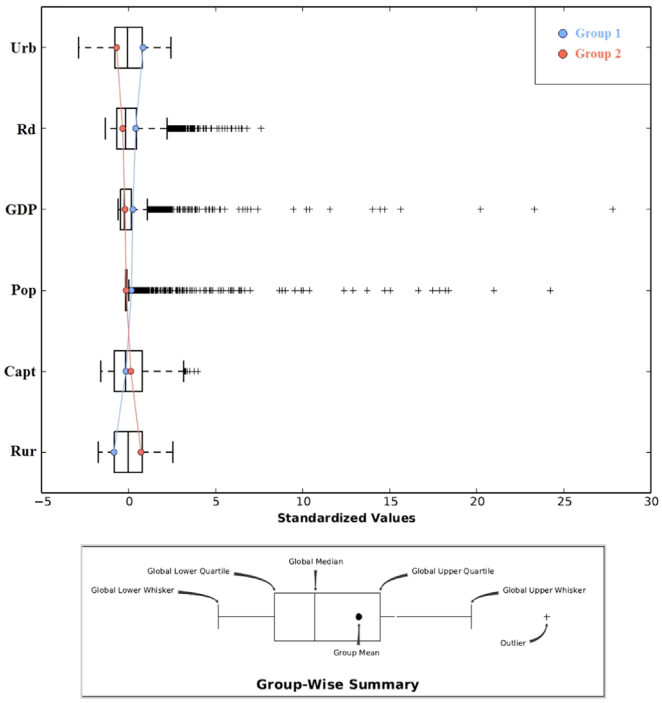

Fig. 4. K mean analysis – summary statistics (parallel box plot). Note: urbanization rate (Urb); rate of highways (Rd); population density (Pop); distance from the capital (Capt); rural population density (Rur). (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

values for distance from the capital; and lower values (first quartile) for rural population density. Group 2 (red) municipalities had lower values (first quartile) urbanization rate; median values for highway density, GDP, and population density; between median and third quartile values for distance from the capital; and higher values (third quartile) for rural population density.

Fig. 5 shows the spatial distribution of the groups and the variables. Overall, most of the municipalities located in the Northwest and Northeast were defined as Group 2 (red); while Group 1 included most of the municipalities from central and South Brazil (blue).

3.4. Vehicle emissions and cardiorespiratory disease risk

Fig. 6 shows the relative risk (primary analysis and sensitivity analysis) of cardiorespiratory disease hospitalization for each quantile (0.05, 0.10, 0.25, 0.50, 0.75, 0.90, and 0.95), for the period between 2008–2012, and considering PM as pollutant. In the Appendix 3–14, we present the relative risk for NMHC, CH_4, NO_x, and CO. We obtained similar results for all five pollutants. In most of the cases, the findings presented decimal differences. For example, considering the primary analysis, quantile 0.75, and the year 2008, we found a risk of 4.42 (95% CI: 3.68, 5.27) associated with CO; 4.45 (95% CI: 3.59, 5.15) for NMHC; 4.65 (95% CI: 3.84, 5.35) for CH_4; 4.09 (95% CI: 3.57, 4.89) for NO_x; and 4.18 (95% CI: 3.66, 4.94) for PM.

For the primary analysis (Fig. 6, panel C.1), only the year 2008 showed significant risk of cardiorespiratory disease hospitalization (p-value ≤ 0.01) in all quantiles of pollutant exposure. We did not find significant risk for the quantile 0.95 in 2009, 2010, 2012 (Fig. 6, panel C.1). We present in Appendix 15–29 the variation in risk along all percentiles.

For the sensitivity analysis in Group 1, we did not find significant cardiorespiratory disease hospitalization risk for the exposure quantiles 0.90 and 0.95 in 2008; and we did not find significant risk for the quantiles 0.75, 0.90, and 0.95 between 2009 and 2012. For the sensitivity analysis in Group 2, however, we found significant risk in all quantiles of pollutant exposure and in all periods studied (Fig. 6).

There were different patterns of risk between group 1 and group 2. For the primary analysis and sensitivity analysis in Group 2, we observed an increasing risk of cardiorespiratory disease hospitalization at the lower quantiles of pollutant exposure (0.05 to 0.50–0.75) and a decreasing risk at the higher quantiles. For the sensitivity analysis in Group 1, the risk was constant at the quantiles below 0.25; above the quantile 0.25, we observed a decreasing risk (Fig. 6).

Taken together, our sensitivity analysis findings suggest higher risks of cardiorespiratory disease hospitalization associated with exposure to vehicle emission pollutants in the Group 2 municipalities and lower risks in the Group 1 municipalities. Overall, these differences were larger at quantiles above 0.10. For example, considering the quantile 0.75 of PM in the year 2008, our results showed a risk of 4.18 (95% CI: 3.66, 4.93) in the primary analysis, with a 0.98 (95% CI: 0.10, 2.05) risk in Group 1 compared to a 5.56 risk (95% CI: 4.46, 6.25) in Group 2 (Fig. 6). For the example above, the risk from Group 2 is approximately 480% higher than the risk from Group 1, and 35% higher than the risk from the primary analysis.

Finally, our findings showed a decreasing risk from 2008 to 2012, especially at the quantiles above 0.25. These findings were larger for the primary analysis (Fig. 6).

4. Discussion

Our findings showed a variation of the spatio-temporal distribution of hospital admissions rate for cardiorespiratory diseases in Brazil, with higher rates in the Northeast, Midwest, and South and lower rates in the Northwest. This distribution was strongly associated with vehicle emissions in Brazil and socio-economic factors. Higher highway and population densities are located in the Northeast, Midwest, and South, and these regions have higher numbers of vehicles, approximately 85% of the national fleet. Our study findings are consistent with other studies that have shown the spatial association between adverse health effects, vehicle emissions, and socio-economic factors (Maantay, 2002; Zandbergen and Green, 2007; Wallace et al., 2009).

We expected to find higher risk of cardiorespiratory disease hospitalization for municipalities in Group 1, due to the higher urbanization rate, highway density, and population density and lower rural population density. However, income (represented by GDP in our study) appeared to be the strongest factor determining the risk of cardiovascular disease related to vehicular emissions. Group 1 had higher GDP values and lower health risks. This finding is similar to other studies that have shown a link between higher income and lower health risks (Powell et al., 2004; Lopez et al., 2006; Campos et al., 2008; Singhe and Jamal, 2012; Branis and Linhartova, 2012; Zou et al., 2014). In addition, disparities in access to health care may be other factor related to our results in Group 1. Other studies have suggested this association (Cao et al., 2011).

Overall, we found that a 15% increase in air pollution is associated with a 6% increase in hospital admissions rates for cardiorespiratory disease. In other words, a 6% increase in tons of PM (considering the quantile 0.75 and the year 2008 as example) would increase the risk of cardiorespiratory disease hospitalization by 0.26 (95% CI: 0.22, 0.31) overall (primary analysis). In Group 1 municipalities, this would amount to a 0.06 (95% CI: 0.07, 0.13) increase in risk compared to a 0.36 (95% CI: 0.30, 0.40) increase in Group 2 municipalities.

Other studies have reported associations between vehicle emissions and cardiorespiratory diseases. For example, in China it was estimated that each 10 $\mu g/m^3$ elevation in PM and NO_x was

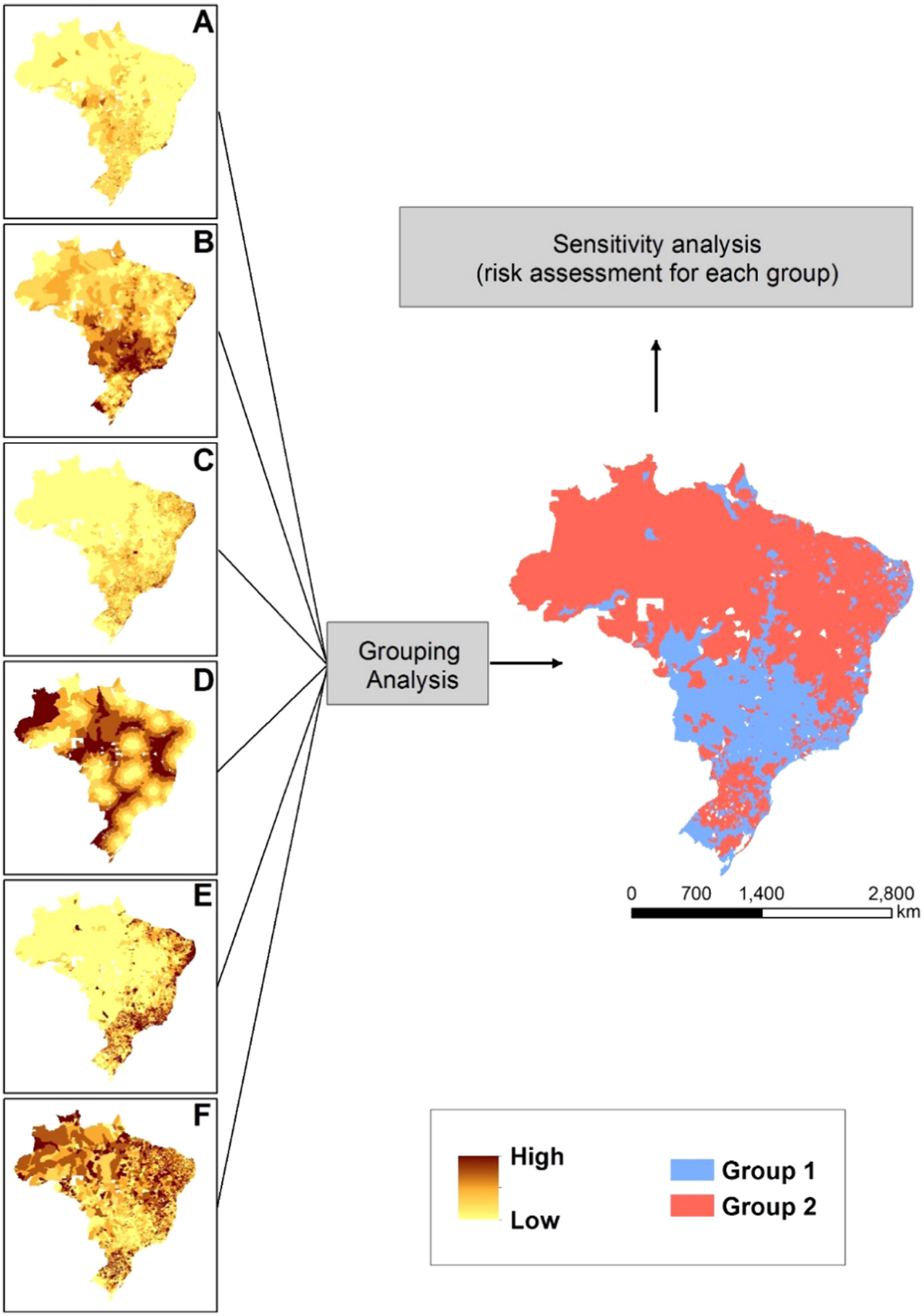

Fig. 5. Grouping analysis – spatial distribution of the groups and variables. Note: GDP (A); urbanization rate (B); rate of highways (C); distance from the capital (D); population density (E); rural population density (F). (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

associated with a 0.9% (95% CI: 0.3%, 1.5%), and 2.3% (95% CI: 0.6%, 4.1%) increased risk of cardiovascular diseases, respectively (Cao et al., 2011). Another study observed 50 million people in the 20 biggest cities in the U. S. and found that each 10 $\mu g/m^3$ elevation in PM was associated with an increase of 0.31% in cardiorespiratory mortality (Dominici et al., 2005). Another study analyzed 43

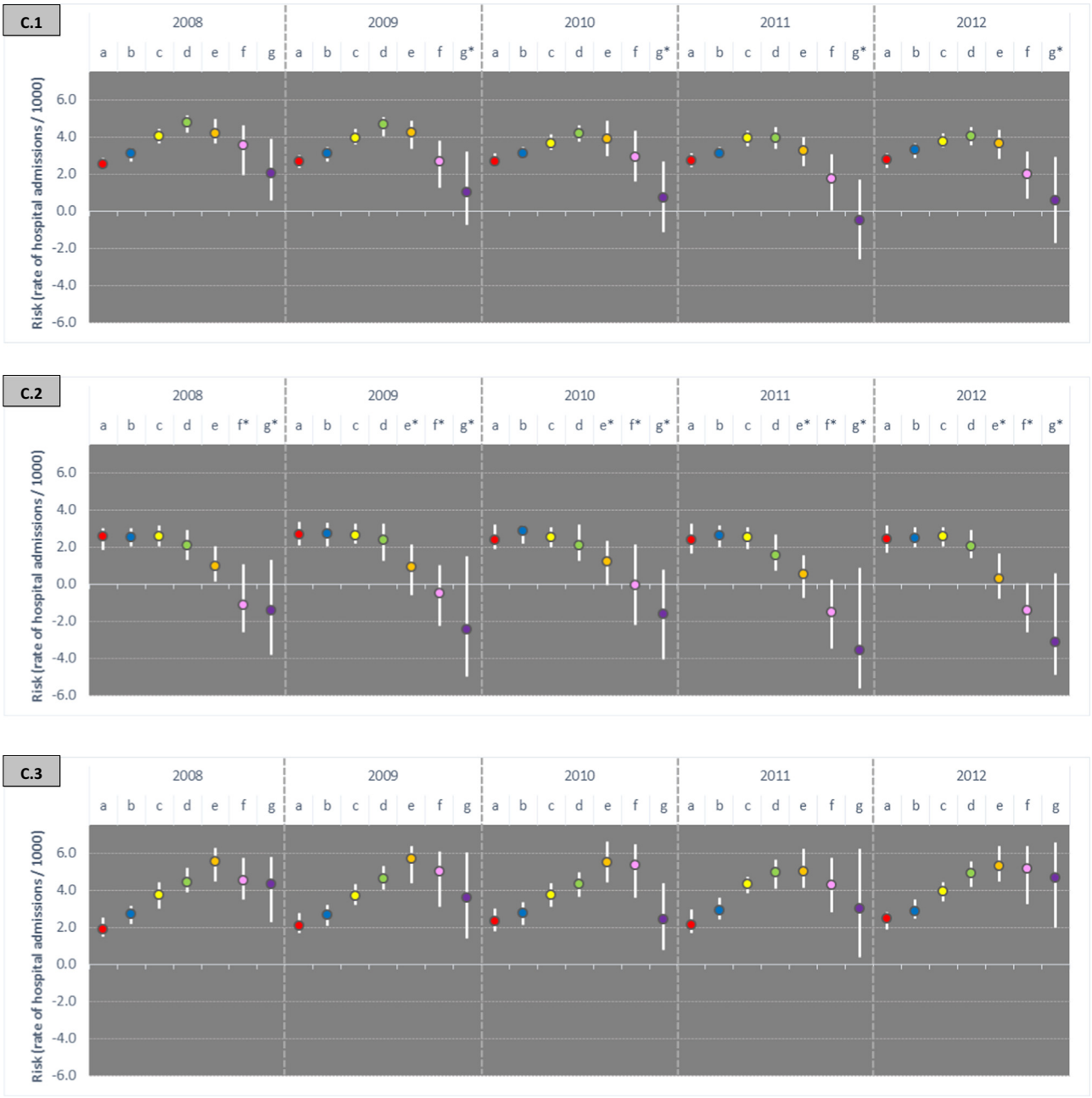

Fig. 6. Risk (rate of hospital admissions/1000) for PM. Notes: Risk from the primary analysis (C.1); risk from the sensitivity analysis – group 1 (C.2); risk from the sensitivity analysis – group 2 (C.3); quantile 0.05 (red dot, and letter "a"); quantile 0.10 (blue dot, and letter "b"); quantile 0.25 (yellow dot, and letter "c"); quantile 0.50 (green dot, and letter "d"); quantile 0.75 (orange dot, and letter "e"); quantile 0.90 (pink dot, and letter "f"); quantile 0.95 (purple dot, and letter "g"); 95% Confidence Interval (white vertical bars); p-value > 0.01 (*). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

million people in 29 European cities and found that a 10 $\mu g/m^3$ elevation in PM_{10} was linked with an increase of 0.69% (95% CI0.31–1.08%) in cardiovascular deaths (Zanobetti et al., 2003). In São Paulo, Brazil, it was estimated that an increase of 24.7 $\mu g/m^3$ in PM_{10} concentration increased the pneumonia admission rate by 9.8% (Nascimento et al., 2006).

Regarding the temporal distribution of our data, we observed that the rate of hospital admissions for cardiorespiratory diseases decreased from 2008 to 2012. One of the possible reasons may be related to environmental policies implemented in Brazil in recent years. Brazil has established two main programs to control and regulate emissions from vehicles (e.g., emission standards, fuel quality etc.): the National Program of Air Quality Control (PRONAR) and the Program to Control Air Pollution from Vehicles (PROCONVE). Positive effects from environmental policies have been reported in other studies, such as Boffetta et al. (2008), Armstrong and Darnton (2008), Gallardo et al (2012) and Vlachokostas et al. (2009).

There are some limitations in our study. First, we did not control for tobacco smoke exposure, which is an important factor in cardiorespiratory disease risk (Lim et al., 2012). Smoking data in Brazil is not available at the spatial level used in our study. Second, we did not control for others socioeconomic status, such as occupation, vehicle ownership, poverty, diet, housing types etc. These data are not available at the municipal level in Brazil. Also, we did not control for covariates at the individual level. Finally, we did not consider direct measurement of air pollution. As we mentioned previously, the air pollution monitoring network in

Brazil has serious limitations. Brazil has 1.3 stations per one-million inhabitants. Among the 5570 municipal districts in Brazil, only 1.7% of them have air pollution monitoring networks.

5. Conclusions

We found a significant association between risk of cardiorespiratory diseases and vehicle emissions in Brazil. Socio-economic factors are important modifiers of this association. Our study provides supports the creation of effective environmental health public policies that take into account the risk factors present in Brazilian municipalities. We suggest that emission control in Brazil should be focused in low income regions.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.envres.2016.06.027.

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