Locational patterns of warehouses in 78 cities around the world, a comparative meta-analysis

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This report is an addition and development of a former research (Dablanc et al., 2020). These are part of the research initiatives performed by the Logistics City Chair. The Logistics City Chair of the University Gustave Eiffel in France investigates urban logistics scientific concerns focusing on urban and suburban logistics real estate and trends and new consumer practices and their impact on urban logistics and real estate. The Chair is a partnership between University Gustave Eiffel (France), Sogaris, Region Ile-de-France.

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1. Introduction

1.1. Context

Locational models and urban morphological and functional structures have been an object of scientific investigation since the beginning of the 19th century. Researchers have started discussions about hierarchical functional distribution and spatial elements, such as the distance between urban areas, to understand the urban structure and evolution of cities' and regions' (Christaller, 1966; Clark, 1967).

Since then, various investigations have considered cities and their regional relations as systems, with the complexity inherent in their form and functions. Batty (2010) explored the understanding of cities as the result of the interaction of subsystems, whose parts can be understood from a more systemic aspect and whose whole is more complex than the sum of the parts. Cities result from the spatial interaction needed for social, cultural, and economic activities to develop and, therefore, for access to urban functions. Furthermore, the connectivity of these functions is crucial for them to be effective, highlighting the need to plan both the location of activities and the connections between them to conform to the urban way of life (Spiekermann & Neubauer, 2002).

In this context, cities' morphological and functional dimensions are structured and involve different aspects of urban life. These dimensions depend on different functions, highlighting economic activity resulting from the needs and desires of citizens' consumption. To sustain consumption, the supply and distribution of goods in an urban context is necessary (Diziain et al., 2012). However, externalities arising from urban commodity distribution (UCD) are significant in the economic, environmental, and social dimensions. Taniguchi et al. (2001) developed the concept of urban logistics to propose solutions for optimizing DUM and promoting the reduction of externalities of this activity (Gatta et al., 2017; Taniguchi, 2001). Among these solutions, those oriented toward installing logistics infrastructure, such as warehouses and distribution centers, stand out. Temporal-spatial dynamics are related to the location of these facilities, and spatial dispersion has been investigated through descriptive spatial statistics, conforming to the methodological approach of measuring logistics sprawl (Dablanc & Rakotonarivo, 2010). Recent studies have discussed the relationship between the spatial structure of logistics facilities and the morphological-functional structure of cities (Giuliano & Kang, 2018; González-Feliu, 2018; Sakai et al., 2016, 2018; Strale, 2020; Woudsma & Jakubicek, 2020). Nevertheless, this report does not focus on methods for measuring logistics sprawl but on finding dynamic patterns in metropolitan cities worldwide and addressing the hypotheses explored in this work.

In this report, we present the research performed by The Logistics City Chair, focusing on two scientific themes: (i) urban logistics real estate and (ii) trends and new practices in consumption, production, and distribution that impact urban logistics and logistics real estate. This study is part of the first theme and included in the Chair's objective: "Logistics sprawl and urban logistics: analysis of territorial dynamics linked to the evolution of the location of logistics activities, at the 'macro' level" (Dablanc et al., 2020).

1.2. Objectives of the research

Generally, in this study, we intend to:

- provide a clean and comprehensive database of freight facilities in large metropolitan areas.
- develop comparative analyses regarding location factors related to logistics facilities and the issues raised based on secondary sources.

Through this research, as a contribution to **theme 1.1 of the Logistics City Chair**, we use this database to **further test seven hypotheses** (made previously by L. Dablanc) **linking urban characteristics and forms to the spatial distribution of warehouses**, namely:

- **H1**: There are more warehouses/pop in large and medium metropolitan regions than in smaller ones.
- **H2**: There are more warehouses in global hub metropolitan regions (or Gateways) than in regular ones.
- **H3**: There are more warehouses in metropolitan regions belonging to mega-regions than in « regular » ones.
- **H4**: The increase in the number of warehouses over time is more significant in medium and large metropolitan regions than in smaller ones.
- **H5**: The increase in the number of logistics facilities over time is positively related to the importance of the role of global logistics hub (or Gateways) played by an urban area.
- **H6**: Logistics sprawl is positively related to the differential in land/rent values for logistics land uses between suburban and central areas in an urban region.
- **H7**: Logistics sprawl is negatively related to the degree of regional logistics land-use control.

To develop this research, we have considered the **previous data collection performed by the Logistics City Chair** concerning metropolitan areas where locational patterns of warehouses, incl. logistics sprawl, were investigated by different research teams and published in scientific journals. This previous dataset (Dablanc et al., 2020) concerned information regarding centrographic sprawl measures, timeframe and sources of data collection, the population in the timeframes, metropolitan administrative details, information on the spatial structure of the metropolitan areas, its importance as a gateway at a regional scale, and aggregated data on logistics facilities rent prices (Figure 1). The **meta-analysis** (Dablanc et al., 2020) considered 74 case studies (metropolitan regions studied in the literature on warehouse locations).

We have then **updated the dataset**, **gathering a total of 78 metropolitan regions** (Figure 2) whose logistics sprawl measures were calculated. The metro areas of Cape Town, Gauteng, eThekwini, and Seoul were added to the previous dataset. Statistical tests were then performed to investigate each hypothesis, and the results are presented in this report. To synthesize this dataset, we systematically reviewed the papers considered in this study and built the elements of a meta-analysis.

This report aims to carry out **(i)** a systematic review of the scientific literature on worldwide logistics sprawl centrographic measure and perform a meta-analysis; and **(ii)** an investigation of the proposed hypotheses, considering the results published on the phenomenon of logistics sprawl in 18 studies and 78 metropolitan areas.

This report is structured in 4 sections, namely: (i) introduction; (ii) methodological approach; (iii) results; and (iv) final considerations.

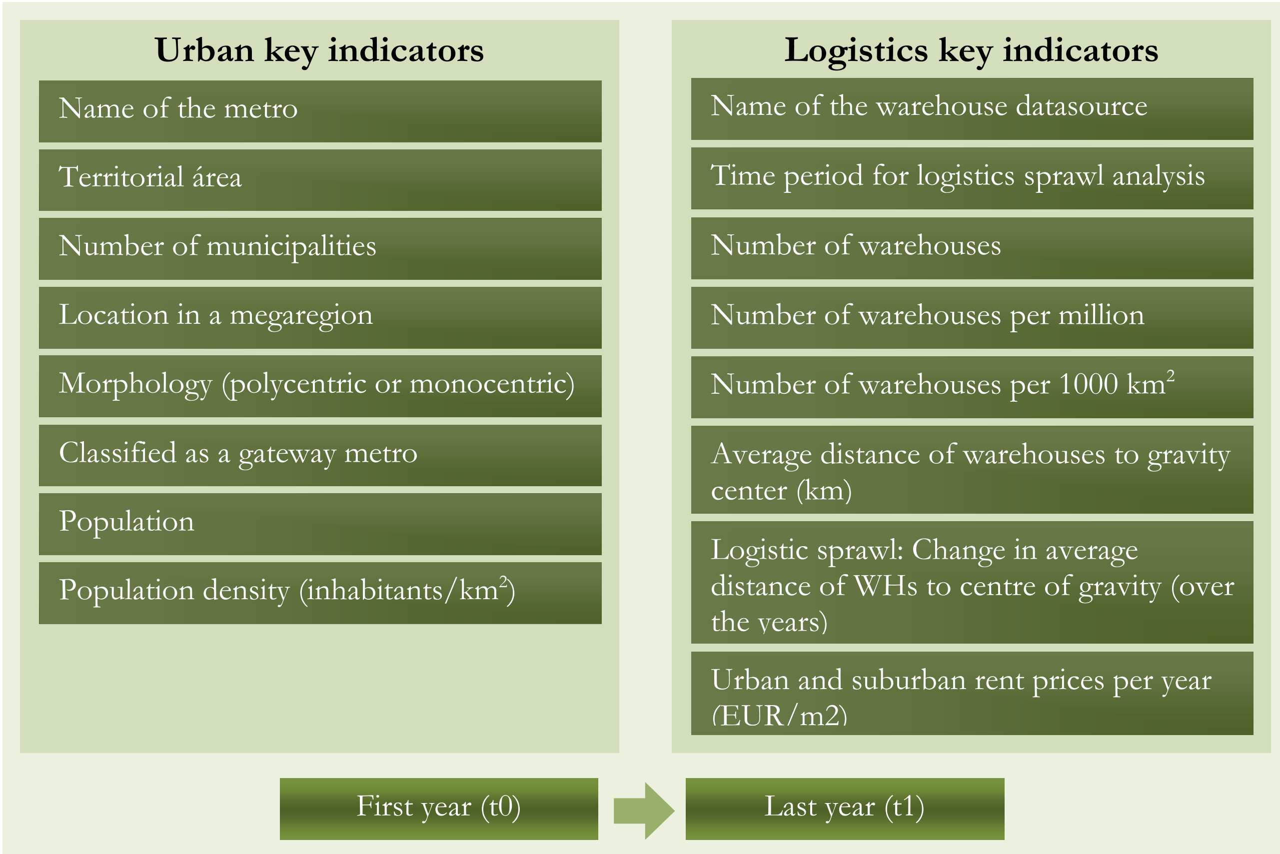


Figure 1: Organizations of the dataset (source : Dablanc et al., 2020)

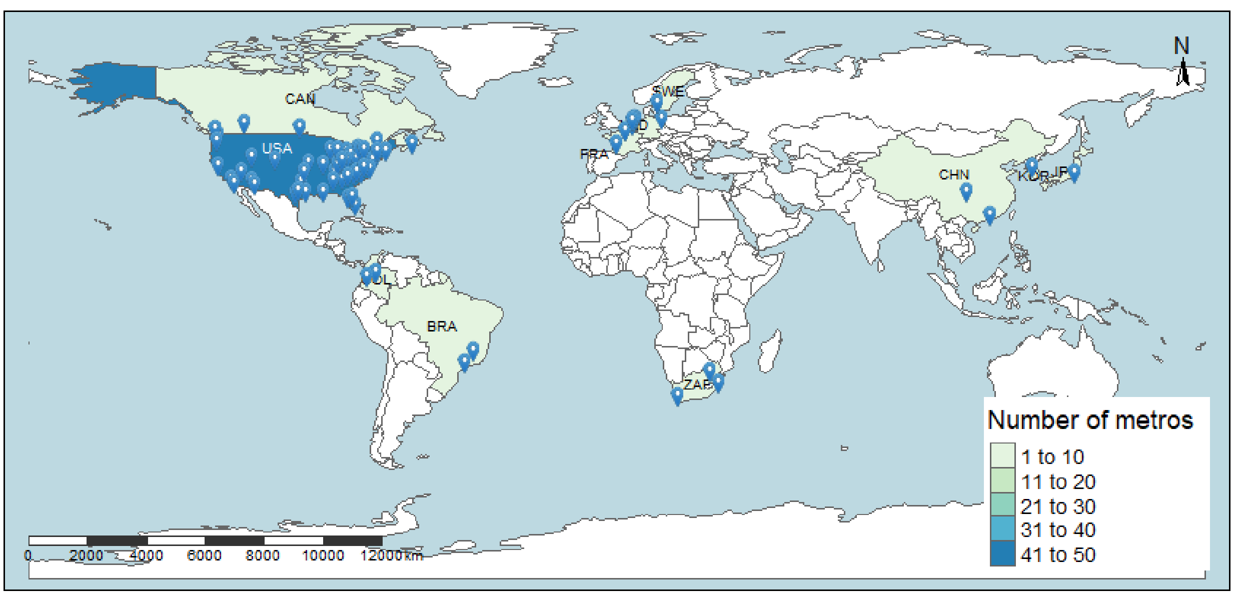


Figure 2: Metropolitan areas with data in the dataset

2. Methods and data

All the methodological steps and decisions are stated while presenting the results. Still, the analytical process was divided into **two main steps**, given in the respective subsections: **(i)** systematic review (meta-analysis); **(ii)** hypotheses investigation.

2.1. A systematic review (meta-analysis)

The literature review can present advantages and disadvantages when review methods are considered, and the implications of the findings are discussed, impacting the usefulness of its results to the field of knowledge. Consequently, the state-of-the-art review must present conceptual and methodological guidelines to fulfill its objectives effectively (Wee & Banister, 2016). Thus, two secondary steps are given in this work to address the investigation and synthesis of the state-of-the-art: (i) a bibliometric analysis of the selected papers and (ii) a systematic literature review, including a meta-analysis.

Systematic reviews are a valuable tool in the social sciences, providing a comprehensive and rigorous approach to synthesizing the existing evidence on a particular research question. They involve a thorough search of relevant studies, a screening process to determine their relevance, a critical quality assessment of the included studies, and a synthesis of the findings to conclude the state of the evidence. They involve defining research questions, conducting a thorough literature search, critically appraising quality, and synthesis of findings. Systematic reviews help inform policy and practice in education, public health, and social services (Walker, 2007).

2.1.1. Selected papers

This work's systematic review was conducted in three stages: planning, execution, and synthesis—the review aimed to consolidate studies that present centrographic measures of logistics sprawl. No search criteria were necessary due to the study's objectivity and the previous data collection, but here we present some studies published after Dablanc et al. (2020) were concluded. In the execution stage, the studies were identified, selected, and classified as eligible (Dablanc et al., 2020). Each relevant article's title, abstract, and full text were reviewed to validate their inclusion in the discussion and synthesis (Dablanc et al., 2020). Finally, in this report, we contribute to updating the dataset with a total of 19 papers, present the objectives, methods, and main findings of each one and the synthesis as a meta-analysis.

2.1.2. Exploring key terms

We have used the R package *litsearchr* (Grames, 2019), which brings different functions for synthesizing literature reviews. These functions help identify search terms and save time selecting keywords. It does this by pulling out the most relevant keywords from articles on the research topic of interest and suggesting them as potential search terms.

First, we built a BibTex file containing each paper's metadata (see *Table 3* below, p. 20), including the title, keywords, abstract, and publication information. These data were assembled as a dataset to be explored and synthesized.

After building the dataset, we searched for the terms that compose the title, keywords, and abstract. Our search intended to gather terms mentioned at least twice and control for terms with at least two words. We have considered the dataset Stopwords ISO Dataset (Diaz, 2020), the most comprehensive collection of stopwords for multiple languages, to focus on actual key terms. The search was performed in English.

The extracted potential keywords were obtained considering at least two words and keywords that appear twice or more in the complete set of results, considering the papers' title, keywords, and abstract. We got 45 terms and narrowed this result by discarding the keywords "freight transportation", "large metropolitan", "logistic facilities", "logistics facility", "paper focuses", and "recent years". There were 39 potential key terms in the final selection.

We then assessed the importance of terms by building a keyword co-occurrence network with a minimum number of studies and occurrences set to 1. We then made a matrix with rows representing the papers and columns describing the terms and illustrated the importance (strength) of the edges in a cord diagram. The 'strength' of each term in the network is the number of other terms it appears with. The network helps identify the frequently co-occurring terms highly connected to others, making them significant to the topic as the strength increases.

One exciting aspect of keyword co-occurrence networks is that their significance metrics follow a power law, in which numerous terms possess low significance and a few are very significant. This power law relationship can be used to identify key terms, and we want to select all more important terms within a certain threshold. Considering the strength of the edges, we determine a cut-off value that limits the inclusion of terms regarding its strength. We used a cumulative method to find the least number of words that give us 60% of the total relevance in the network. We proposed a cut-off searching for the 40% highest strengths in the network and got the 16 strongest terms within the papers.

2.1.3. Exploring the data

An additional attempt was made to synthesize the results of studies that measured logistics sprawl quantitatively. This methodological step explores the information relative to the dataset assembled (Dablanc et al., 2020). The meta-data from previous work is presented in Table 1.

Table 1: Dictionary of variables

Variable Name	Description
metro	The name of the metropolitan area.
mega_region	The name of the mega-region to which the metropolitan area belongs.
country	The name of the country of the metropolitan area is located.
continent	The name of the continent in which the metropolitan area is located.
data_sources	The sources of data used to compile this dataset.
area (km2)	The total area of the metropolitan area in square kilometers.
number_mun	The number of municipalities included in the metropolitan area.
size	The size of the metropolitan area (small, medium, or large).
urban_centrality	Categories for urban morphology (polycentricity or monocentricity) of the metropolitan area.
gateway	Whether the metropolitan area is considered a gateway city.
time_period_start	The start year of the period covered by the dataset.
time_period_end	The end year of the period covered by the dataset.
years_data	The number of years covered by the dataset.
population_t0	The population of the metropolitan area at the start of the period covered by the dataset.
number_ware_t0	The number of warehouses in the metropolitan area at the start of the period covered by the dataset.
gravity_t0	Centrographic measure of the metropolitan area at the start of the period covered by the dataset.
population_t1	The population of the metropolitan area at the end of the period covered by the dataset.
number_ware_t1	The number of warehouses in the metropolitan area at the end of the period covered by the dataset.
gravity_t1	Centrographic measure of the metropolitan area at the end of the period covered by the dataset.
log_sprawl	Binary variable for logistics sprawl.
log_sprawl_measure	Logistics sprawl measure in the metropolitan area.
avg_price	The average price of logistics real estate in the metropolitan area.
central	Whether the observation is in the central area of the metropolitan area.
suburban	Whether the observation is in the suburban area of the metropolitan area.
diff	The difference between the average price of real estate in central and suburban areas of the metropolitan area.
sprawl_year	Logistics sprawl per year.
quad	A categorical variable indicates the metropolitan area's quadrant based on its yearly sprawl level and differential warehouse rental prices.

As techniques considered for the meta-analysis, we used: descriptive statistics and cluster analysis (k-means). To address the synthesis of the metropolitan regions through the data, we have selected three variables whose effects are jointly investigated in this work: (i) measurement of sprawl (log_sprawl_measure); and (ii) the mean number of warehouses considering the two periods in time (number_ware_t0 and number_ware_t1). The complete dataset had 78 observations (the metropolitan areas identified in the selected papers). Nevertheless, two metropolitan areas had to be excluded (Cali and Brussels) since no data on the number of warehouses in t0 were available. Also, the data on the

Randstad region is represented by the regions Flevoland, Noord Holland, Utrecht, and Zuid Holland, so four metro areas for this megaregion (the data for the megaregion is not included). Therefore, our dataset for the cluster analysis concerned 75 observations.

Cluster analysis is a statistical tool within multivariate statistics. This tool is practical and straightforward for identifying data patterns. This work intends to understand warehouse location patterns among metropolitan areas regarding independent and dependent variables. The algorithms are designed to include more similar observations in a group that differs from others. K-means is a centroid-based clustering interactive method, and the number of groups needs to be specified by the researcher.

The Elbow Method supports identifying the most favorable number of clusters in a dataset for clustering algorithms, particularly k-means. This method aids in locating the "elbow point" in the graph relating the number of clusters versus the corresponding within-cluster sum of squares (WCSS) (Humaira & Rasyidah, 2020; Syakur et al., 2018), which represents the number of clusters that bring most of the information. We considered this method to determine the number of clusters for a starting point to perform the K-means algorithm.

K-means is sensitive to scale, and all features must be on the same scale. To treat scale, we have standardized the variables related to the number of warehouses and the logistics sprawl measure considering the MinMax algorithm.

To check for the robustness of the cluster analysis considering the 75 observations, we decided to rerun the investigation regarding the dataset without outliers. The method K-means clustering is sensitive to outliers. Therefore, we have considered the interquartile range criterion (IQR) to determine and exclude the outliers. All observations outside interval I (Equation 1) are considered potential outliers. Some metropolitan areas with essential characteristics for this analysis were reincluded in the dataset.

$$I=[q_{0.25}-3\cdot IQR\ ;\ q_{0.75}+3\cdot IQR] \qquad \text{Equation 1}$$

To assess the quality of the clustering analysis, we have considered the between sum of squares (ss for the distance among clusters centroids) and within sum of squares (ss for the distances among observations and the centroid of one cluster). A good clustering should have internal cohesion and external separation, meaning the between_SS/total_SS ratio should approach 1.

When there are more than two dimensions or variables, the function "fviz_cluster" will conduct principal component analysis (PCA) and display the data points on a plot based on the first two components.

Principle Components Analysis is a tool that allows the summarization and visualization of data sets with many variables. It reduces the dimensionality of datasets aiming at identifying a new coordinate system by linear transformations, in which most of the variation in the data can be explained in fewer dimensions. PCA works by identifying the directions in which the data varies the most, which are called principal components. The first principal component captures the most variation in the data, the second principal component captures the second-most variation, and so on. The variance in PCA refers to the amount of variation in the original data that is captured by each principal component (Hair, 2006).

2.2. Hypotheses investigation

Initial exploratory data analysis was performed for the key logistics indicators (i) number of warehouses, (ii) number of warehouses per million inhabitants, (iii) number of warehouses per km^2; (iv) logistics sprawl measure; and (v) logistics sprawl per million inhabitants.

We performed exploratory data analysis for each of these variables and presented the results in the respective section.

Figure 3 presents the methodological approach proposed for the exploration of the hypotheses.

It is essential to highlight that Figure 3 and the steps described in the following three sections of this work do not entirely explain the methodological approach developed to investigate H6—the method described in the respective section (3.2.6) and can be accessed in Oliveira et al. (2022).

For the hypotheses that consider the increase in warehouse number (H4 and H5), we could not assess the relationship between time and dependent variables since we have investigated the differences considering t0 and t1.

Also, hypothesis H7 was not explored in this work since further information on logistics land-use control for the metropolitan areas was unavailable.

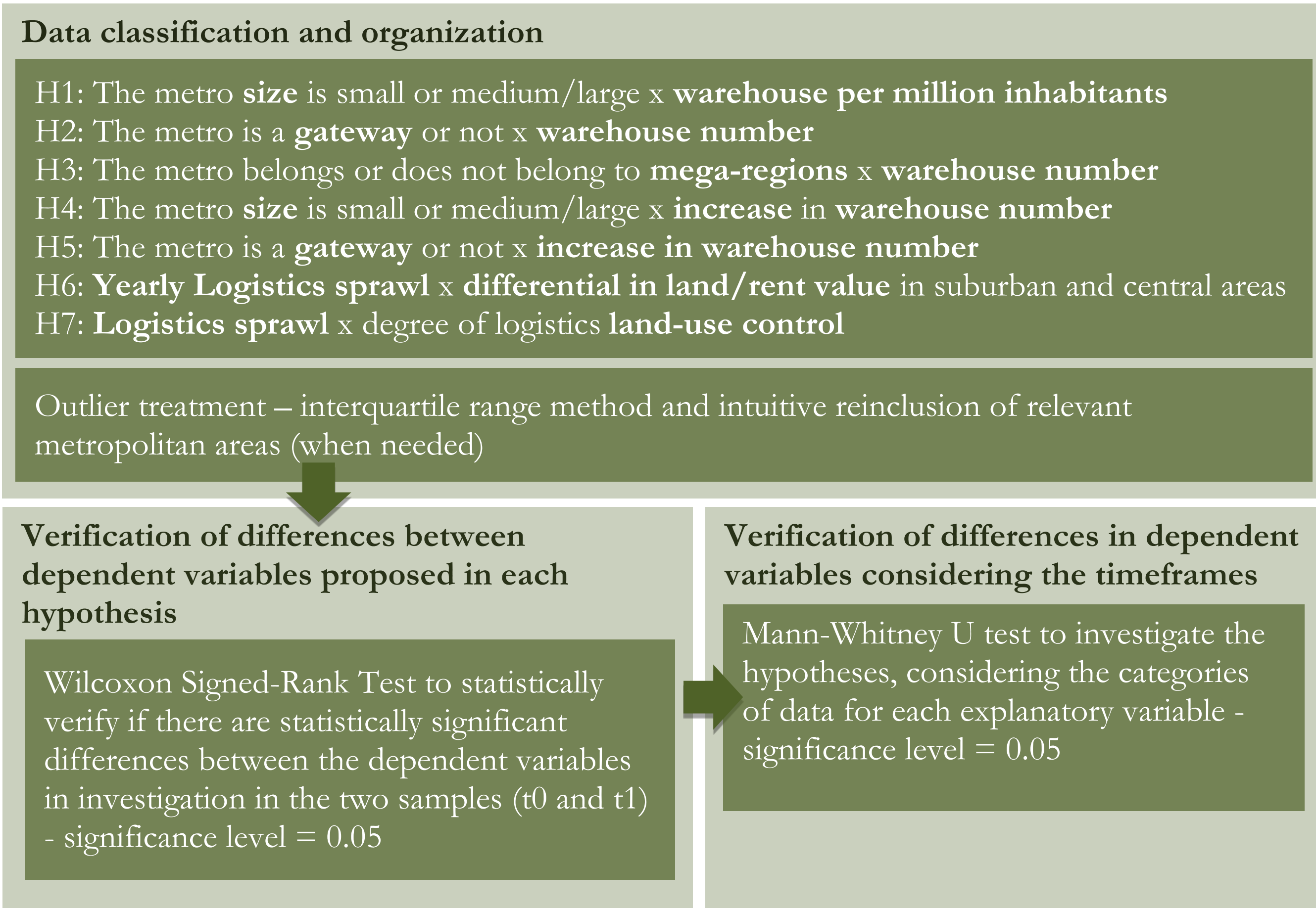


Figure 3: Methodological approach to investigate the hypotheses.

2.2.1. Data classification

Considering the hypotheses under investigation, we have classified the meta-data available (Dablanc et al., 2020; Oliveira et al., 2022) according to the independent variables in the data, namely: (i) metro size; (ii) metro status as a gateway/global hub; (iii) metro location in mega-regions; and (iv) differential rent value in central and suburban areas. The possibilities of categories are presented in Table 2.

Table 2: Classification of independent variables

Independent variable	Categories
Metro size	Small Medium/Large
Metro's status as a gateway/global hub	Yes No

Metro location in mega-regions	Yes No
Differential rent value in central and suburban areas	Higher prices in Activity Hubs (AH) Higher prices in Peripheral Activity Zones (PAZ) No significant differential price

The **dependent variables** considered in this work, related to the hypotheses, are (i) **warehouse per million inhabitants**; (ii) **warehouse number**; (iii) **increase in warehouse number**; and (iv) **yearly logistics sprawl.**

We have then treated the outliers within each subset of the available data since the observations could be an outlier in one variable, not another. We have considered the interquartile range criterion (IQR) to determine and exclude the outliers. All observations outside interval I (Equation 1 – section 2.1.3) are potential outliers.

With the data organized for each hypothesis investigation, we moved to analyze the relationship of variables.

2.2.2. Verification of differences in dependent variables considering the timeframes

For each hypothesis, we have checked if we could state that the means of the dependent variables in the first year of data collection and the last one could be considered the same. In other words, we could ask: is time somehow related to each dependent variable?

We considered using a paired t-test to test whether the dependent variable in t0 significantly differed from the same one for t1. Nevertheless, considering some hypotheses, the difference in the values for each metro was not normally distributed (Shapiro-Wilk test and histograms) (Ross & Willson, 2017). We ran the Wilcoxon Signed-Rank Test for all hypotheses, considering complete data and the one without outliers (Hogg & Tanis, 2010; Pestana, 2014).

The Wilcoxon Signed-Rank is a non-parametric statistical test used to compare two related samples. It is often used when the data does not meet the assumptions of a parametric test, such as the paired t-test. The test determines whether the median difference between two paired samples is zero (Hollander et al., 2014; Krzywinski & Altman, 2014; Montgomery & Runger, 2011; Scheff, 2016). This test was chosen because the two samples (t0 and t1) are related, coming from the same metropolitan area at different times, but the differences are not normally distributed.

The assumptions for this test are: (i) the observations are mutually independent; (ii) the data are paired and from the same population; and (iii) the data can be measured on at least an interval scale. They are met in all investigations. The null hypothesis (H0) of the Wilcoxon Signed-Rank Test indicates that the dependent variables are equal at time 0 and time 1. We considered a significance level of 5% in all analyses.

2.2.3. Verification of mean differences between dependent variables proposed in the hypotheses

The Welch two-sample t-test was the first choice to compare the dependent variable in the categories for the metros in each hypothesis. However, the assumptions for performing the Welch two-sample t-test indicated that the data must be $n > 30$ or normally distributed, which is not present in some hypotheses. Therefore, we decided to consider the Mann-Whitney U test to check if the dependent variables are the same, comparing different categories of independent variables.

The Mann-Whitney U is a non-parametric statistical test used to compare two independent samples, and it is a choice when the data does not meet the assumptions of a parametric test. This test compares two independent samples to verify whether their medians are equal. In our case, the dependent variables are related to the categories (independent variables), resulting in different groups of metropolitan areas. The assumptions to use the Mann-Whitney U test (also known as the Wilcoxon rank-sum test) are that: (i) the variables being compared must be continuous; (ii) samples should be independent; and (iii) sample sizes of, at least, five observations (Hogg & Tanis, 2010; Krzywinski & Altman, 2014; Montgomery & Runger, 2011). In this test, the H0 is that there is no difference between the two groups.

We considered a significance level of 5% in all analyses, which is the most common significance level used in hypothesis testing is 0.05 (5%). The significance level is the probability of making the error type I. This error concerns the probability of rejecting the null hypothesis when it is true. Choosing a 5% significance level balances the risk of making a Type I error and a Type II error. The last one is failing to reject the null hypothesis when it is false) (Montgomery & Runger, 2011).

3. Results

3.1. A systematic review (meta-analysis)

3.1.1. Selected papers

The selected papers for this work, following the premises presented in the method (section 2.1.1), are listed in Table 3. After this table, we present the discussion of the papers.

Table 3: Papers of the metanalysis

Authors	Title	Publication year	Publication
Andriankaja, D.	Le desserrement logistique, quelle responsabilité dans l'augmentation des émissions de CO2 des activités de messagerie ?	2014	[Phdthesis]. University of Paris-East.
Dablanc, L., Ogilvie, S., & Goodchild, A.	Logistics Sprawl: Differential Warehousing Development Patterns in Los Angeles, California, and Seattle, Washington.	2014	Transportation Research Record: Journal of the Transportation Research Board, 2410(1), 105–112.
Dablanc, L., & Ross, C.	Atlanta: A mega logistics center in the Piedmont Atlantic Megaregion (PAM).	2012	Journal of Transport Geography, 24, 432–442.
Daraviña, P. A. C., & Suescún, J. P. B.	Logistic sprawl and polarization in Colombian urban areas.	2016	Proceedings WCTR.
Dubie, M., Kuo, K. C., Giron-Valderrama, G., & Goodchild, A.	An evaluation of logistics sprawl in Chicago and Phoenix.	2020	Journal of Transport Geography, 88, 102298.
Guerin, L., Vieira, J. G. V., de Oliveira, R., de Oliveira, L., Vieira, H. E. de M., & Dablanc, L.	The geography of warehouses in the São Paulo Metropolitan Region and contributing factors to this spatial distribution.	2021	Journal of Transport Geography, 91, 102976
Heitz, A., & Dablanc, L.	Logistics Spatial Patterns in Paris: Rise of Paris Basin as Logistics Megaregion	2015	Transportation Research Record: Journal of the Transportation Research Board, 2477(1), 76–84.
Heitz, A., Dablanc, L., Olsson, J., Sanchez-Diaz, I., & Woxenius, J.	Spatial patterns of logistics facilities in Gothenburg, Sweden.	2020	Journal of Transport Geography, 88, 102191.

Heitz, A., Dablanc, L., & Tavasszy, L. A.	Logistics sprawl in monocentric and polycentric metropolitan areas: The cases of Paris, France, and the Randstad, the Netherlands.	2017	Region, 4(1), 93.
Klauenberg, J., Elsner, L. A., & Knischewski, C.	Dynamics of the spatial distribution of hubs in groupage networks – The case of Berlin.	2018	Journal of Transport Geography, May 2017, 102280.
Li, G., Sun, W., Yuan, Q., & Liu, S.	Planning versus the market: Logistics establishments and logistics parks in Chongqing, China.	2020	Journal of Transport Geography, 82, 102599.
Oliveira, L., Santos, O., Oliveira, R., & Nóbrega, R.	Is the Location of Warehouses Changing in the Belo Horizonte Metropolitan Area (Brazil)? A Logistics Sprawl Analysis in a Latin American Context.	2018	Urban Science, 2(2), 43.
Kang, Sanggyun.	Exploring the contextual factors behind various phases in logistics sprawl: The case of Seoul Metropolitan Area, South Korea.	2022	Journal of Transport Geography.
Sakai, T., Kawamura, K., & Hyodo, T.	Logistics Facility Distribution in Tokyo Metropolitan Area: Experiences and Policy Lessons.	2016	Transportation Research Procedia, 12, 263–277.
Strale, M.	Logistics sprawl in the Brussels metropolitan area: Toward a socio-geographic typology.	2020	Journal of Transport Geography, 88, 102372.
Trent, N. M., & Joubert, J. W.	Logistics sprawl and the change in freight transport activity: A comparison of three measurement methodologies.	2022	Journal of Transport Geography, 101, 103350.
Woudsma, C., & Jakubicek, P.	Logistics land use patterns in metropolitan Canada.	2020	Journal of Transport Geography, 88, 102381.
Woudsma, C., Jakubicek, P., & Dablanc, L.	Logistics sprawl in North America: Methodological issues and a case study in Toronto.	2016	Transportation Research Procedia, 12, 474–488.
Xiao, Z.	Remarking urban logistics space: E-tailing and supply chain revolution in the case of Shenzhen, China	2017	[Phdthesis]. The University of Hong Kong.
Yuan, Q., & Zhu, J.	Logistics sprawl in Chinese metropolises: Evidence from Wuhan.	2019	Journal of Transport Geography, 74, 242–252.

In 2012, Dablanc and Ross suggested a method for analysing the spatial distribution of freight and logistics operations, considering planning and policy concerns. They found that local and regional authorities face challenges in including logistics activities in their planning processes. The article shares various findings, such as the extent of logistics sprawl, the concentration of logistics activities, and the spatial arrangement of logistics facilities in Atlanta and the Piedmont Atlantic Megaregion. The paper also discusses the difficulties that suburban Atlanta planners encounter when promoting logistics activities, the planning and policy issues that arise concerning logistics activities, and how local and regional authorities take them into account during planning (Dablanc & Ross, 2012). Regarding the North American experience, we still have the works of Dablanc et al. (2014), Dubie et al. (2020), and Woudsma & Jakubicek (2020).

Dablanc et al. (2014) aimed to compare the shift in the location of warehouses in the Los Angeles and Seattle Metropolitan Areas from 1998 to 2009. The study explored logistics sprawl, which involves migrating logistics facilities away from central business districts. The research mapped the location of warehouses in each time frame and determined the distance between them and the barycenter. It analyzed data from the US Census County Business Patterns and used statistical analysis to identify the factors contributing to these changes. The study found that Seattle experienced clustering and increased concentration of warehousing activity, while Los Angeles experienced logistics sprawl, generating additional vehicle-miles travelled, congestion, CO_2 emissions, and local atmospheric issues (Dablanc et al., 2014).

Dubie et al. (2020) aimed to investigate factors that influence the location choices of warehouses in metropolitan areas, such as public policies, demography, land price, and supply chain costs. The work also aims to evaluate whether there is a tendency for logistics sprawl, which refers to moving warehouses away from urban centers to more suburban and exurban areas. The authors measured logistics sprawl for Chicago and Phoenix metropolitan areas. In Chicago, warehouse establishments multiplied between 1998 and 2013, with the highest growth occurring in Will and Cook counties. To measure sprawl, the barycenter (weighted geographic mean) was calculated for all establishments and warehousing establishments for both years. The study determined that the average distance between the barycenter and the warehouse establishments had risen by nearly 9 km. The results for Phoenix show that warehousing in the area experienced considerable growth between 1998 and 2015, and the barycenter of warehousing establishments sprawled approximately 2.7 km west.

Woudsma and Jakubicek (2020) explored Vancouver, Calgary, Montreal, Winnipeg, and Halifax metropolitan regions, in Canada. Spatial data on logistics firms and their employment levels were obtained for each location. Indicators based on descriptive spatial statistics, such as the average center of establishments and standard distance, were explored, and the results showed that in smaller metropolitan areas, such as Winnipeg and Halifax, there was no sprawl concerning land use and the development of logistics activities. In the other cities, moderate evidence of sprawl occurred. (Woudsma & Jakubicek, 2020).

The same authors invited Dablanc to explore Toronto as a case study for investigating the spatial patterns of freight and logistics activities in North America. The paper compares the sprawl patterns of warehouses to all businesses in the Greater Toronto Area (GTA) and the Greater Golden Horseshoe (GGH) over ten years. The results show that warehouses in the GGH sprawled faster than other businesses, and in 2012, warehouses were, on average, farther away from the center than all businesses (Woudsma et al., 2016).

Moving to the European context, Dablanc and Rakotonarivo (2010) and Andriankaja (2014) analyze the evolution of courier agency locations in Île-de-France from 1974 to 2010, focusing on major courier groups serving Paris. The study utilized La Poste's yellow pages archives to obtain addresses of courier agencies and conducted a spatial statistical analysis to describe their spatial distribution and dispersion. The findings indicate that the standard distance of courier agency seedlings has increased from 6.3 km in 1974 to 18.1 km in 2010, and the degree of dispersion is almost three times higher in 2010 than in 1974. Accessibility was identified as the primary factor for logistics facility location, with 80% of messaging agencies in the inner and outer suburbs located less than 5 km from the nearest expressway access (Andriankaja, 2014).

Still concerning Paris, Heitz et al. (2015) examine the spatial distribution of freight and logistics facilities in the Paris region and the Paris megaregion between 2000 and 2012. The study analyses the growth of warehousing and logistics facilities in both areas and how it contributes to defining a larger urban region or megaregion. The paper also discusses the role of freight hubs in connecting international and urban supply chains and how it affects the locational patterns of logistics and warehousing facilities in Paris. The main findings concern the significant increase in the number of warehousing and logistics facilities in both the Paris region and the Paris megaregion between 2000 and 2012. The growth of these facilities illustrates both centrifugal processes, from the urban core to the suburban and exurban areas of the region, and centripetal processes, from the margins of the Paris basin to the edges of the Paris region. The study also found that freight hubs play a crucial role in connecting international and urban supply chains, which explains part of Paris's locational patterns of logistics and warehousing facilities (Heitz & Dablanc, 2015).

Heitz et al. (2017) investigate the difference in logistics sprawl between monocentric and polycentric systems of cities by comparing two cases, the Paris region in France, representative of a monocentric urban development, and the Dutch Randstad area as a polycentric case. The study explores the reasons that may explain the difference and concludes that urban structure, spatial planning policies, and the freight hub quality of a region are factors of influence (Heitz et al., 2017). The authors compare the difference in logistics sprawl between monocentric and polycentric systems of cities by investigating the growth and suburban relocation of warehousing activities. The paper contributes to establishing the distinction between 'logistics sprawl' and 'logistics suburbanization.'

Further exploring European metropolitan regions, Strale (2020) analyzes the geography of logistics in the Brussels metro area and highlights the suburbanization of logistics activities, which creates land consumption, longer supply chains, and job shifts. The author constructs a spatial typology to understand the evolution of the Brussels metropolitan logistics space. The author uses quantitative and qualitative methods to collect and analyze data, including GIS analysis, statistical analysis, and interviews with logistics professionals. The results highlight the growth of logistics activities in the Brussels metropolitan area, illustrating the pursuit for agglomeration of logistics facilities around main cities, even if the geography has evolved within the metropolitan areas. The authors also identify the links between the evolution of the geography of logistics activities with socio-demographic conditions and the political structure of Brussels (Strale, 2020).

Kauenberg *et al.* (2018) proposed an analysis of the dynamics of the spatial distribution of logistics hubs in groupage networks in Berlin and the surrounding municipalities of Brandenburg, as well as the reasons behind the relocation of these facilities. The authors use quantitative and qualitative methods, including mapping and calculating the distance between logistics hubs and their barycentre and conducting expert interviews to identify reasons for relocation. The results show that the number of logistics hubs outside of Berlin has increased, and the mean distance between service providers and the barycentre has also increased. The reasons for relocation include the need for large expanses of industrial land in Berlin, the quest for good infrastructure connections to motorways and federal highways, lower traffic disruption in Brandenburg, and lower land prices. The authors suggest that policy and land-use planning could influence the relocation of logistics facilities (Klauenberg et al., 2018).

Heitz et al. (2020) investigate the warehouse geography in Gothenburg, Sweden. The objective was to examine the aspects of logistics expansion in the metropolitan area by relating the location patterns of logistics facilities to the role of freight and land use policies, considering 2000 and 2014. The average distance to the barycenter grew by 3.4 kilometers in this period. When the city is represented economically and concerning regional integration, it becomes attractive to establish logistics facilities and companies to supply the urban population, making that city a reference for the metropolitan region and generating regional impacts (Heitz et al., 2020).

Exploring South American cities, we have the studies of Daraviña & Suescún (2016), Guerin et al. (2021), and Oliveira et al. (2018). Daraviña & Suescún (2016) investigated the evolution of land use and the role of logistic settlements in the urban area of Bogotá. A centrographic analysis and directional distribution were performed to determine establishments' weighted geometry center and decentralization. However, the research had various obstacles due to dispersed and heterogeneous data, unclear classification codes, and overlapping codes. The authors found that logistic establishments grew by 37% from 2005 to 2011, and logistic clusters were densified along principal corridors. Accessibility was important for geographic logistic distribution, with facilities mainly concentrated along the railway (Daraviña & Suescún, 2016).

Guerin et al. (2021) analyze the spatial distribution and factors influencing the relocation of warehouses in the São Paulo Metropolitan Region (SPMR), Brazil, between 1992 and 2017. The paper proposes a methodological approach, including tools such as spatial statistics, boxmaps, Univariate Local Moran's I, and Local Differential Moran's I, to characterize changes in the region's spatial patterns of logistics facilities. The study aims to provide insights for policymakers and practitioners to improve logistics management and mitigate the negative consequences of logistics sprawl. Among other findings, a positive correlation between logistics sprawl and cargo theft was perceived, indicating the need for in-depth analysis in further studies. The paper also highlights the negative impacts of logistics sprawl on urban freight transport and citizens' well-being, such as increased distance travelled by trucks, increased CO_2 emissions, and more incidence of cargo theft. (Guerin et al., 2021).

Also, for the Brazilian context, Oliveira et al. (2018) analyze the logistics sprawl phenomenon in the Belo Horizonte Metropolitan Area between 1995 and 2015 through spatial analysis. The study explores the spatial correlation between socioeconomic data and the location of warehouses. It defines the service areas of the warehouses, considering a maximum distance through the network of 5, 10, and 15 km. The study also uses spatial cluster analysis to identify the concentration of warehouses along the railroad and road infrastructure and estimate the population the warehouses served. The results show a logistics sprawl indicator of 1.2 km (17.8 km in 1995 and 19 km in 2015). In addition, the study found that most of the warehouses were located within a two-kilometer buffer from the axis of the road and in a five-kilometer buffer from the railroad. Finally, the 15-km service area covered 89% of the population in the study area (Oliveira et al., 2018).

Going to Asia, Li et al. (2020) examine the spatial distribution of logistics land uses and activities in Chongqing, China. They evaluate whether planned logistics parks have attracted logistic establishments sufficiently to change the city's overall geography of logistics activities. The methodology used in this paper involves calculating the density of logistics establishments in each geographic unit and tracking the changes in such density during the observation period. The study also examines two dimensions of logistics sprawl-decentralization and deconcentration to understand the spatial relocation of logistics establishments. Average distance to barycenter and Gini coefficient are used to measure these two dimensions. The authors found that planned logistics parks did not significantly affect the location of logistics establishments in Chongqing, China. The density of logistics establishments increased in the central urban area and decreased in the suburban areas during the observation period. The study also found that the decentralization of logistics activities increased while the deconcentration of logistics activities decreased (Li et al., 2020).

Yuan & Zhu (2019) investigate the logistics sprawl in major metropolitan areas in China, using Wuhan as a case study. The study also examined the factors that affect warehousing location choice, including transport access, land availability, industrial connections, and land use policies. The paper uses geospatial techniques to measure the magnitudes of changes in the decentralization, deconcentration, and spatial clustering of warehousing facilities in Chinese megacities during the last two decades. The authors also develop an econometric model to identify the major factors that shape the spatial distribution of warehouses. The paper confirms the logistics sprawl pattern in Wuhan due to interactions between land use policymaking, changes in urban structure, and technological adaptation. The spatial expansion and spatial clustering of warehouses may lead to more concentrated truck activities in the suburbs, which can have negative environmental and social implications. Also, transport access, land availability, industrial connections, and land use policies are all significantly associated with warehousing development (Yuan & Zhu, 2019).

Still in China, Xiao (2017) explores the relationship between e-tailing and logistics sprawl in Shenzhen, a city with poor infrastructure. Overall, this study highlights the complex relationship between e-tailing and logistics sprawl and offers policy recommendations to mitigate the negative impacts of logistics sprawl. It underscores the importance of governments proposing a joint policy framework to promote regional cooperation on logistics and warehouse activities, investigating the effects of logistics sprawl on the environment, and considering how to bring logistics activities back to the city (Xiao, 2017).

Seoul is the last Asian metropolitan area explored in the selected studies. Kang (2022) explores the phenomenon of logistics sprawl in the Seoul Metropolitan Area, South Korea, which involves building large-scale, automated facilities on the urban periphery to cope with the increasing demand for processing large freight volumes through globalized production and distribution systems. The paper examines the spatial dynamics of warehouse development over the last three decades, and four phases in the spatial dynamics of warehouse development are documented: stagnation (1991-1998), sprawl (1998-2007), peak (2007-2008), and return (2009-present). Four factors behind logistics sprawl are also identified: logistics restructuring driven by a consumption-based economy, location factor trade-offs, disruptive economic shocks, and regulatory reform.

Trent & Joubert (2022) were the only authors to explore African metropolitan regions. These authors examine the assumed link between increased logistics sprawl and increased freight transport activity. Since this link could influence policymaking to fight or facilitate logistics sprawl, this paper investigates the implications of using different methodologies to quantify this relationship. Three different methods are compared. The first two are from well-respected sources in literature, and the third is a contribution of this paper. The methods measure transport activity related to logistics sprawl in three urban areas in South Africa between 2010 and 2014. The results contradict the proposed method, questioning the link between logistics sprawl and freight transport activity. Comparing the methods also shows that it is essential to include empirical data of actual vehicle movement when investigating logistics sprawl's impact on transport activity (Trent & Joubert, 2022).

3.1.2. Exploring key terms

After presenting the selected papers, we explore each work's key terms in the title, abstract, and keywords. We then extract the potential keywords with at least two words that occur at least twice in these textual elements, as presented in section 2.1.2. We got 45 terms and narrowed this result by discarding the redundant or irrelevant keywords, as stated in the method section. The remaining 39 terms are presented in

Table 4.

Table 4: First selection of keywords

average distance	logistics facility location	spatial patterns
centrographic analysis	logistics geography	spatial statistics
directional distribution	logistics industry	standard distance
distribution centers	logistics space	statistical analysis
exurban areas	logistics sprawl	supply chains
facility location	logistics system	urban areas
freight facilities	measure sprawl	urban centers
freight transport	metropolitan areas	urban freight
large metropolitan areas	monocentric urban	urban freight transport
locational patterns	north American	urban logistics
logistics activities	Paris region	urban sprawl
logistics businesses	spatial deconcentration	urban supply
logistics facilities	spatial distribution	warehousing establishments

The relevance of keywords was then determined by creating a keyword co-occurrence network with a minimum number of studies and occurrences set to 1, as presented in section 2.1.2. The strength of each term in the network represents the number of other terms with which it appears (edges). Figure 4 shows the cord diagram with all 39 potential key terms and the strengths as the edges' width.

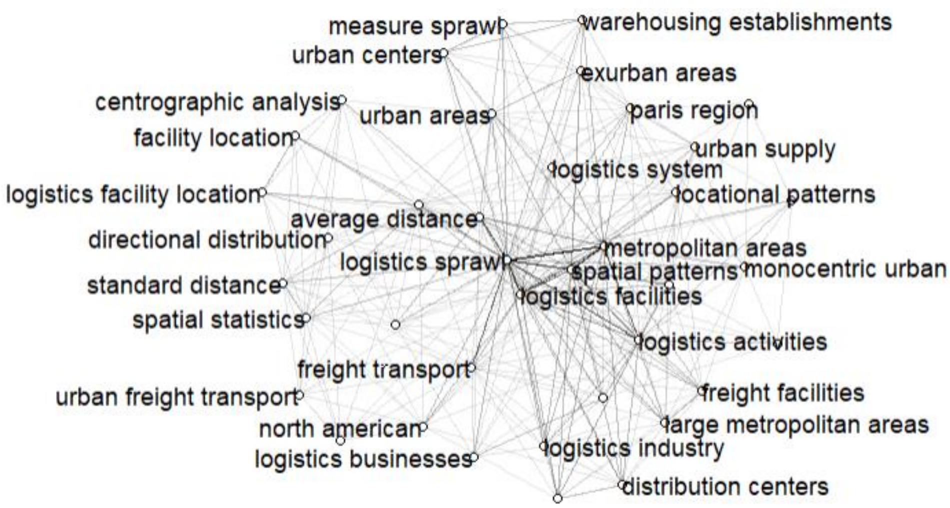


Figure 4: Cord diagram representing the strengths of the edges.

Next, we reduce our graph to only include terms with a node strength above the cut-off value, as presented in section 2.1.2 (40% of the terms represented 60% of all strength). We got the 16 strongest terms within the papers (Table 5).

Table 5: 40% terms with higher strength – 60% of the total strength

Term	Strength	Rank	Class
logistics sprawl	49	16	measure
metropolitan areas	38	15	urban
logistics facilities	36	13	logistics
spatial patterns	36	13	urban
logistics activities	28	12	logistics
average distance	18	10	measure
supply chains	18	10	logistics
distribution centers	17	5	logistics
freight facilities	17	5	logistics
freight transport	17	5	logistics
large metropolitan areas	17	5	urban
spatial deconcentration	17	5	measure
logistics industry	16	4	logistics
Paris region	12	3	urban
spatial distribution	11	1	measure
urban areas	11	1	urban

In Figure 5, we present a visual representation of the reduced graph.

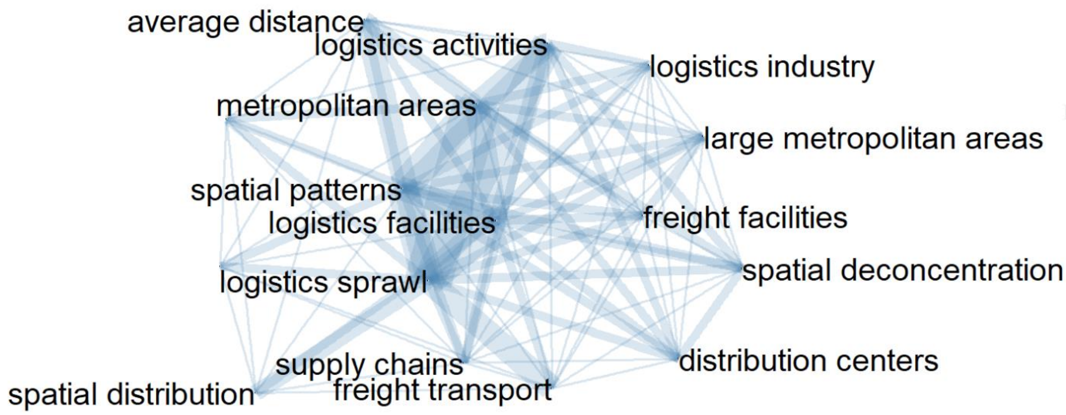


Figure 5: Cord diagram representing the most important keywords.

Given the graph, we can understand that the terms "logistics activities", "spatial patterns", "logistics facilities", "logistics sprawl", "average distance", and "metropolitan areas" are the ones that present the most robust connections. Further investigation can consider these key terms for a new search of publications related to logistics sprawl research.

3.1.3. Exploring the data

An additional attempt was made to synthesize the results of studies that measured logistics sprawl quantitatively. This section explores the data published in previous studies (see Appendix A). As techniques considered for the meta-analysis, we used: descriptive statistics and cluster analysis (k-means). Data regarding the variables (log_sprawl_measure, number_ware_t0, and number_ware_t1) are consolidated in Table 6 and further considered for the cluster analysis.

Table 6: Complete dataset

#	Metro	Number of ware-houses in t0	Number of ware-houses in t1	Logistics sprawl measure
1	atlanta	132	401	4.35
2	belo horizonte	44	156	1.20
3	berlin	18	22	3.98
4	bogota	347	475	0.57
5	bordeaux	11	22	5.60
6	brussels	NA	10553	2.50
7	calgary	21	59	3.50
8	cali	NA	27	0.50
9	chicago	217	415	8.80
10	chongqing	401	3490	16.00
11	flevoland	60	59	NA
12	gothenburg mea	132	207	4.20
13	gothenburg vgc	261	390	2.70
14	halifax	6	9	1.10
15	los angeles	220	515	9.75
16	montreal	79	70	0.30
17	noord holland	318	278	NA

18	paris all	713	955	4.10
19	paris parcels	93	93	11.80
20	phoenix	41	183	2.74
21	sao paulo	228	2066	0.10
22	seattle	85	212	-1.29
23	shenzhen	1430	1660	1.23
24	randstad	589	583	NA
25	tokyo	420	209	4.20
26	toronto ggh	217	350	9.50
27	toronto gta	165	228	1.20
28	utrecht	43	61	NA
29	vancouver	135	134	4.20
30	winnipeg	26	41	0.00
31	zuid holland	168	185	NA
32	new york	938	914	3.27
33	washington dc	285	318	3.14
34	san francisco	305	349	1.22
35	boston	290	294	2.61
36	philadelphia	288	340	2.01
37	dallas	338	402	-0.82
38	miami	193	235	5.91
39	detroit	196	210	5.02
40	houston	221	298	2.46
41	cleveland	148	150	0.05
42	san diego	84	86	-0.93
43	st louis	148	144	-2.91
44	pittsburgh	92	98	2.03
45	denver	118	147	-0.68
46	portland	160	163	1.21
47	tampa	63	79	-0.26
48	orlando	75	91	-0.37
49	kansas city	159	153	4.46
50	columbus	208	195	0.48
51	cincinnati	112	122	-0.43
52	indianapolis	121	171	0.00
53	milwaukee	101	98	7.24
54	charlotte	124	145	3.07
55	salt lake city	88	117	0.31
56	san antonio	47	67	4.44
57	virginia beach	90	98	-2.12
58	las vegas	51	80	9.80
59	new orleans	77	83	10.44
60	nashville	116	121	2.08
61	raleigh	76	77	0.14
62	greensboro	88	88	-3.67
63	louisville	81	89	-0.32
64	grand rapids	62	72	2.37
65	buffalo	57	57	0.00
66	austin	38	50	2.04
67	birmingham	47	51	3.94
68	greenville	101	97	-3.20
69	rochester	45	48	-0.56
70	albany	54	48	0.45
71	dayton	54	49	7.13
72	richmond	58	87	1.45
73	tulsa	39	37	4.02
74	tucson	33	55	-10.86
75	cape town	3899	4349	1.73
76	eThekwini	2673	2733	-0.25
77	gauteng	8401	8766	1.52
78	seoul	984	3340	4.10

After standardizing the variables, we explored the graphic linking the number of clusters and the WCSS (Figure 6), with the normalized variables without outliers. From a visual perspective, we consider k = 5 as the starting point for the analysis.

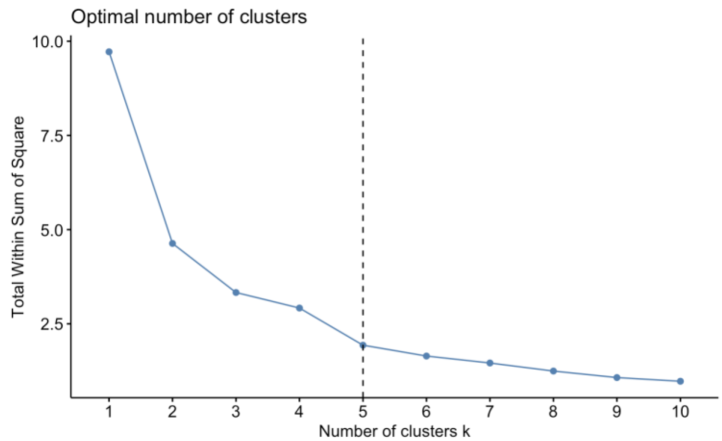


Figure 6: Elbow method to determine the optimal number of clusters considering standardized without outliers variables.

The K-means method results, considering 5 clusters, had a ratio between_SS/total_SS of 80.1%, which is a good result relating cohesion and differentiation.

Figure 7 and

Table 7 present five groups of metropolitan regions. The first group, in pink, regards the metros with the highest average logistics sprawl, the highest number of warehouses in the last year and the second highest in the first year. Group 2, in orange, presents the metros with the lowest score for the number of warehouses in both timeframes and the second highest for logistics sprawl. In light green, the third group presents a low number of warehouses' average score and the lowest average logistics sprawl. The fourth group, in purple, shows the metros with the highest score for the number of warehouses in the first year, the second largest average score for the number of warehouses in the last one, and the second lowest average score for logistics sprawl. Finally, group 5, in dark green, presents the metros with intermediary scores for all variables.

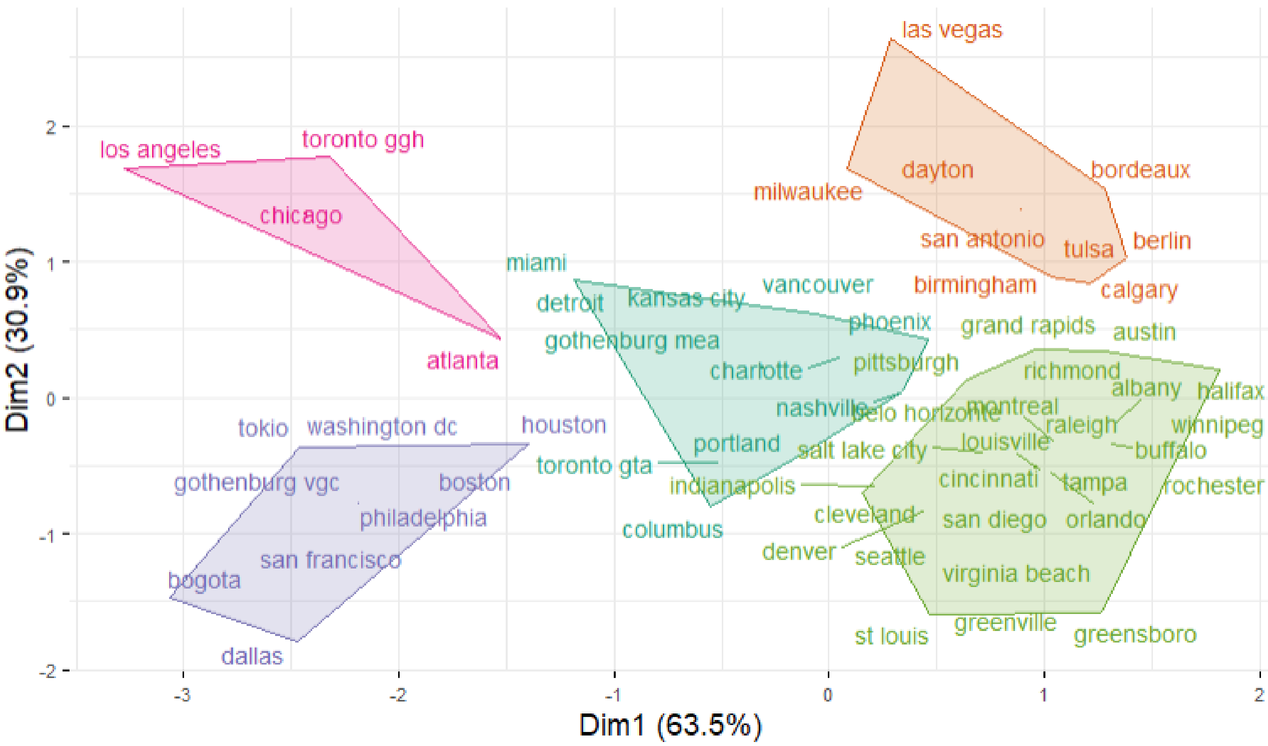


Figure 7: Clusters with standardized and without outliers

Table 7: Average scores for each variable and group

Groups	Color	Number of warehouses in the first year	Number of warehouses in the last year	Logistics sprawl
1	Pink	0.46	0.81	0.88
2	Orange	0.09	0.09	0.68
3	Light Green	0.18	0.18	0.26
4	Purple	0.73	0.66	0.43
5	Dark green	0.34	0.34	0.51

3.2. Hypotheses investigation

In this section we present the results for each methodological step addressing the hypotheses under investigation.

3.2.1. Exploratory data analysis

The first step was to work with exploratory data analysis (EDA) tools. In Figure 8 to 10 we present the number of warehouses, the number of warehouser per million inhabitants, and the number of warehouses per km^2, respectively, in each time frame, for each metropolitan area in the dataset.

Also, in Figure 11 and Figure 12, we can see the logistics sprawl measures and logistics sprawl per million inhabitants, respectively, for each metropolitan area.

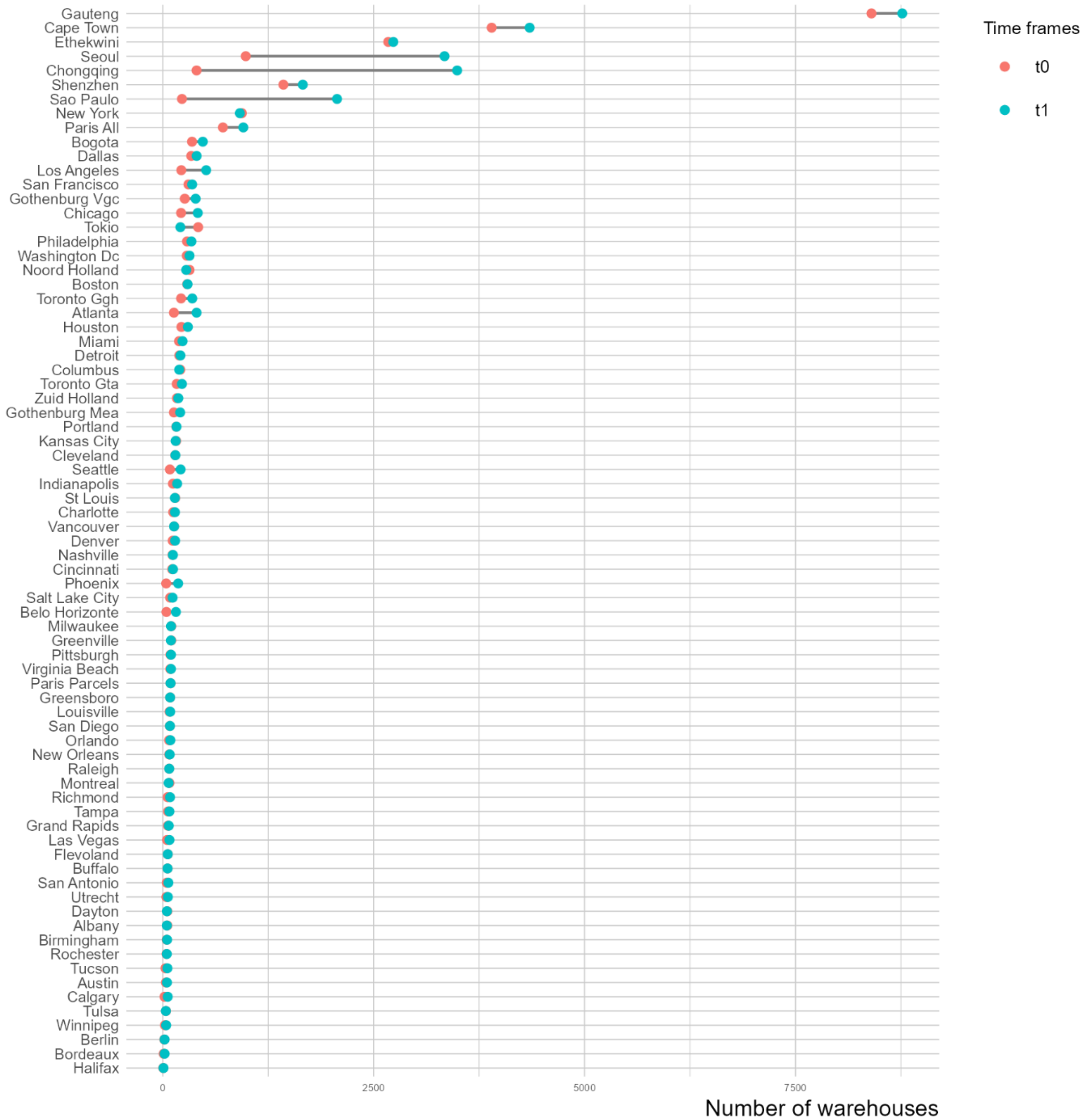


Figure 8: Number of warehouses (timeframes t0 and t1) for each metropolitan area of the dataset

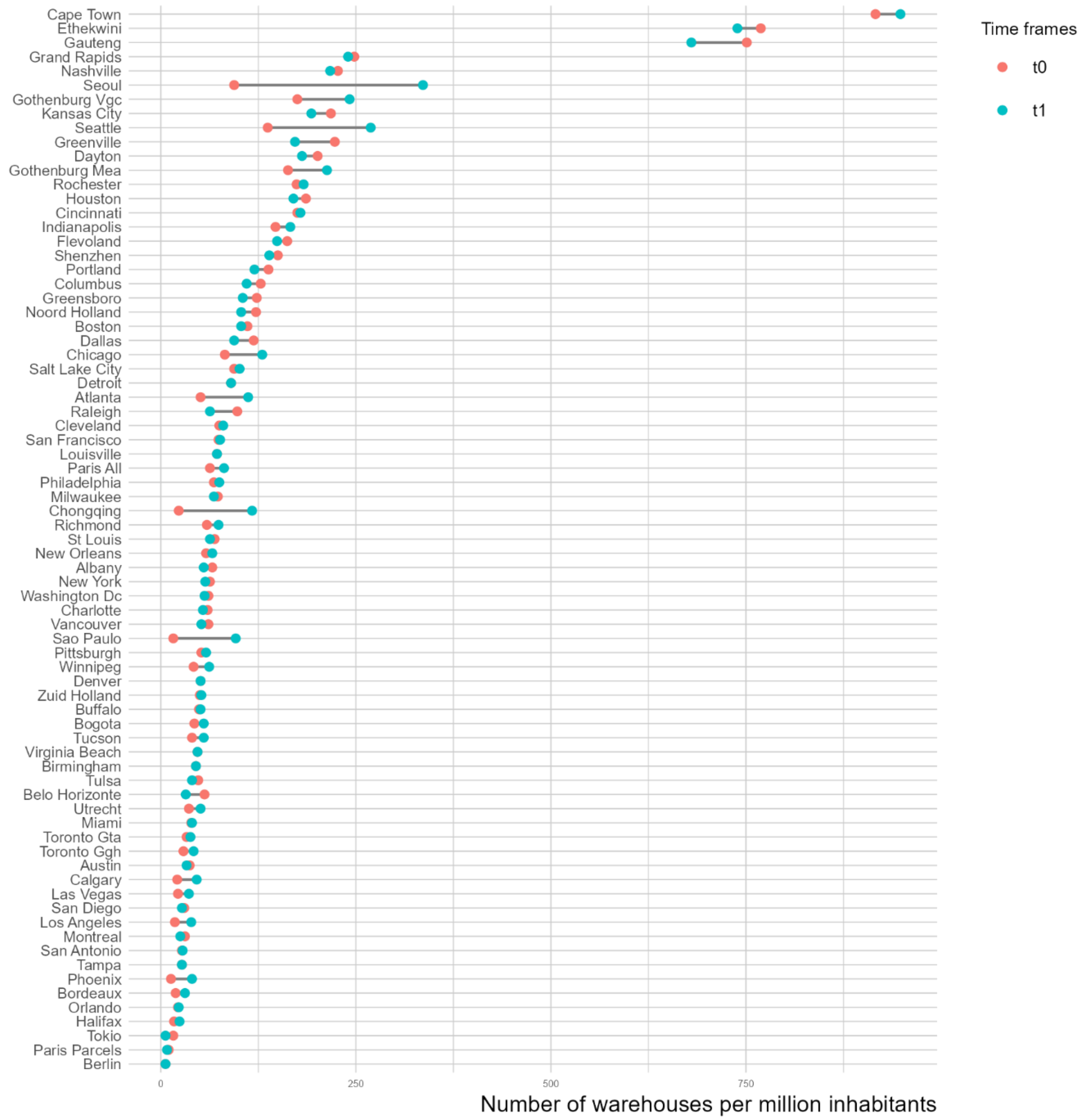


Figure 9: Number of warehouses per million inhabitants for each metropolitan area of the dataset

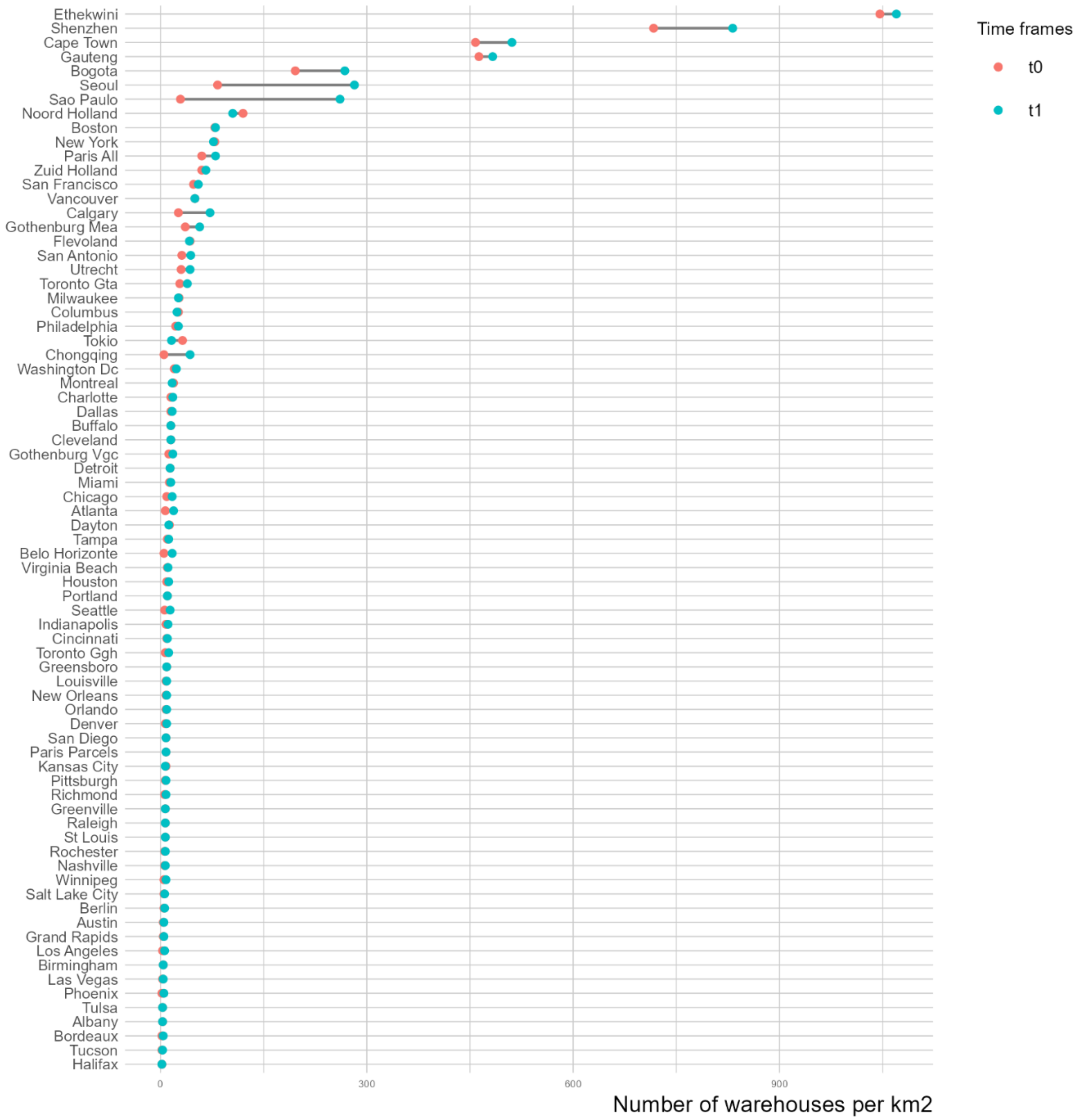


Figure 10: Number of warehouses per km² for each metropolitan area of the dataset

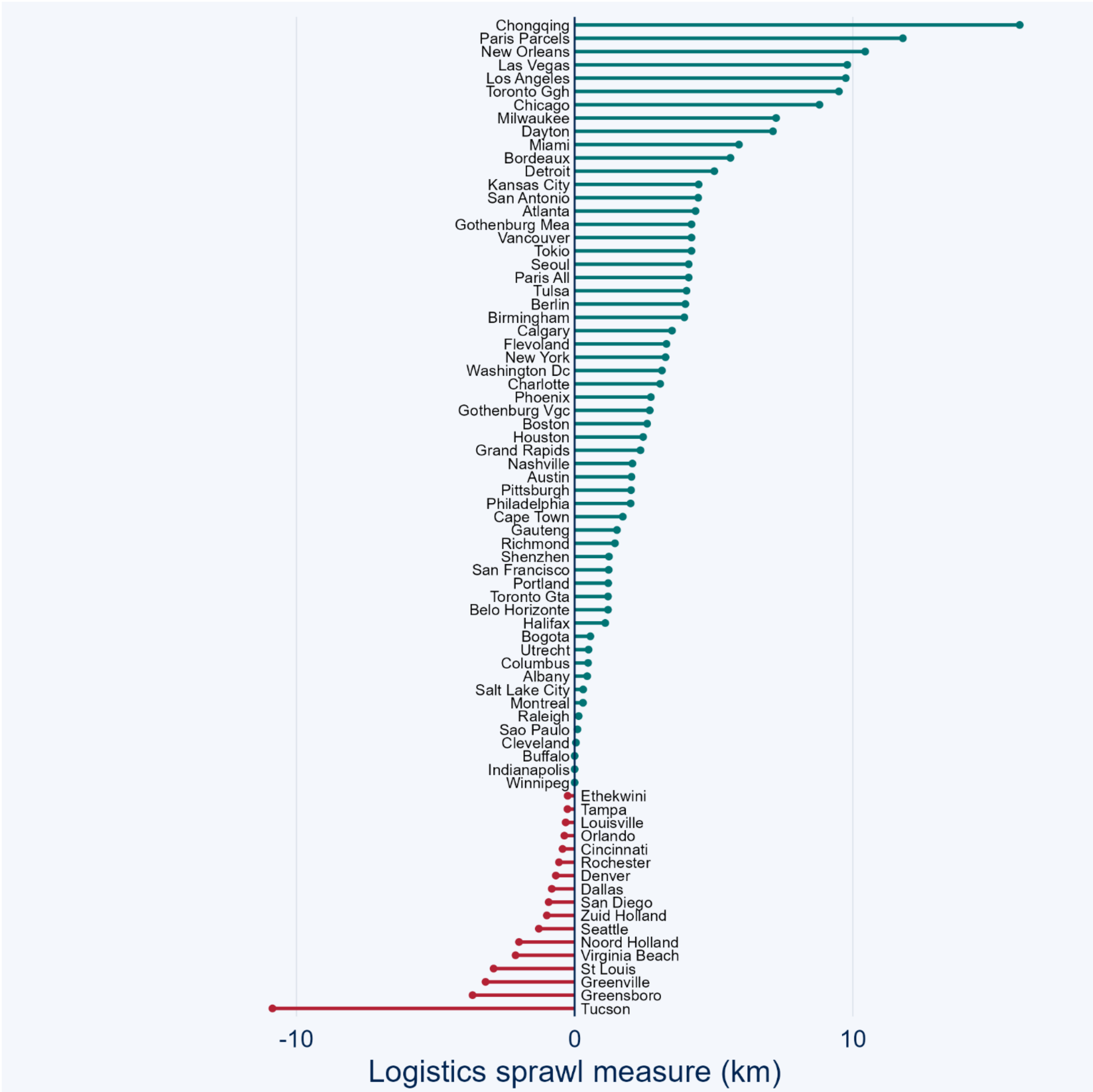


Figure 11: Logistics sprawl measure for each metropolitan area of the dataset

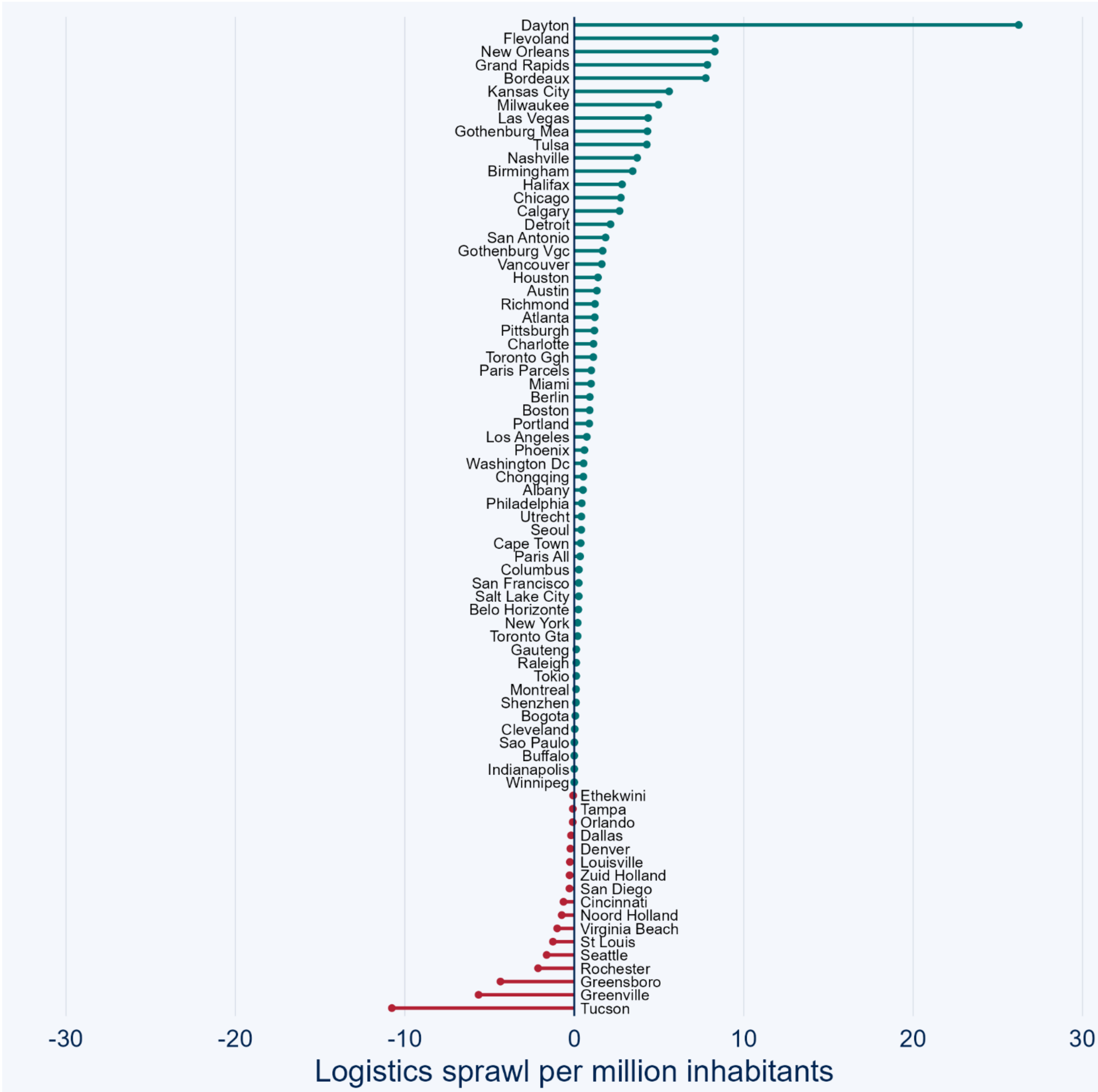


Figure 12: Logistics sprawl per million inhabitants for each metropolitan area of the dataset

Observing the data among metropolitan areas and the central tendency and dispersion measures (Table 8), we can notice a significant dispersion with extreme values in the upper top of the data. Therefore, for the investigation of each hypothesis, we firstly treated the occurrence of outliers.

Table 8: Central tendency and dispersion measures for each variable

Statistics	Number of warehouses		Warehouse per million inhabitants		Warehouse per km²		Logistics sprawl measure	Logistics sprawl per million inhabitants
	t0	t1	t0	t1	t0	t1		

Mean	374.10	517.40	109.50	117.40	55.89	68.59	2.31	1.27
Std. deviation	1094.81	1262.25	157.02	155.24	160.10	174.89	3.91	4.02
Minimum	6.00	9.00	6.00	6.00	2.00	2.00	-10.86	-10.77
25%	59.00	78.00	36.50	43.50	6.00	7.00	0	0
50%	116.00	145.00	61.00	66.00	9.00	14.00	1.73	0.42
75%	221.00	308.00	125.50	125.00	28.50	42.50	4.10	1.51
Maximum	8401.00	8766.00	916.00	948.00	1046.00	1070.00	16.00	26.23

3.2.2. H1: There are more warehouses and more warehouses per million inhabitants in large and medium metropolitan regions than in smaller ones

The variables considered to analyze hypothesis H1 are presented in Table 9.

Table 9: Variables considered to explore hypothesis H1

Variable Name	Description
metro	The name of the metropolitan area.
size	The size of the metropolitan area (small, medium, or large).
number_ware_t0	The number of warehouses in the metropolitan area at the start of the period covered by the dataset.
number_ware_t1	The number of warehouses in the metropolitan area at the end of the period covered by the dataset.

The excluded metropolitan areas (outliers) are **Shenzhen, Chongqing, Sao Paulo, Cape Town, eThekwini, Gauteng, and Seoul** (upper outliers) from the sample. Following the criteria for identifying outliers, **New York and Paris all** were considered outliers. Nevertheless, we did include these metropolitan areas in the clean dataset for this analysis. The average number of warehouses for the remaining sample (68 metros) is presented in Table 10.

Table 10: Average number of warehouses, metro classification, and timeframe – H1 number of warehouses

Data	Time	The average number of warehouses	Size	
			Small	Medium/ Large
Complete	t0	374	49	407
	t1	518	62	564
Without outliers	t0	148	49	158
	t1	183	62	196

As detailed in section 2.2, we have explored the differences in dependent variables between t0 and t1 and the difference in dependent variables regarding the categories. The results of the two approaches are presented in Table 11.

Table 11a: Statistical tests and results – H1 number of warehouses

Objective	Test	p-value	Interpretation
Dependent variables x timeframes	Wilcoxon Signed-Rank Test	1.284e-08 (complete data) 4.364e-07 (no outliers)	We can reject the null hypothesis since the p-value is lower than 0.05. **We have sufficient evidence that the number of warehouses in t0 differs from t1.**
Dependent variables x categories	Mann-Whitney U test	0.003171 (complete data) 0.005518 (no outliers)	We can reject the null hypothesis since the p-value is lower than 0.05. **We have sufficient evidence to state that the number of warehouses in small metro areas differs from medium/large ones.**

In Table 11a, we can verify that both tests indicate that we can reject the null hypothesis. Therefore, regarding time, we can state that **the average number of warehouses in the first year differs from that in the last year**. This information can also be verified in Figure 13, where the median and the distribution of metros considering the number of warehouses, differ. This figure was generated for the data without the aforementioned metropolitan areas as outliers.

Considering the second test for this H1 alternative hypothesis (number of warehouses), we can state that **the number of warehouses in medium and large metros is higher than in small ones**, at a significance level of 5%. In *Figure 14*, we can notice the differences between the average and the median number of warehouses for both categories of metros, confirming the H1.

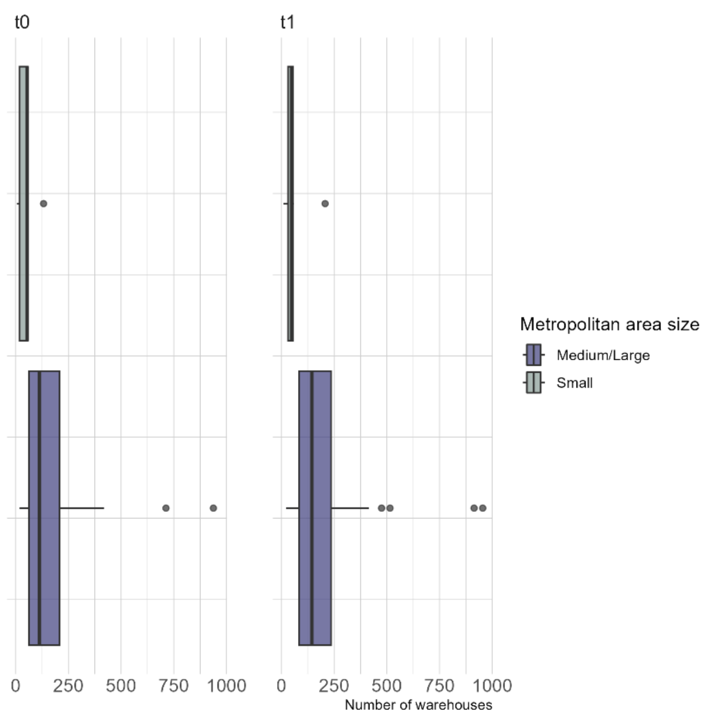


Figure 13: Boxplot for the number of warehouses in different categories of metros and time – H1

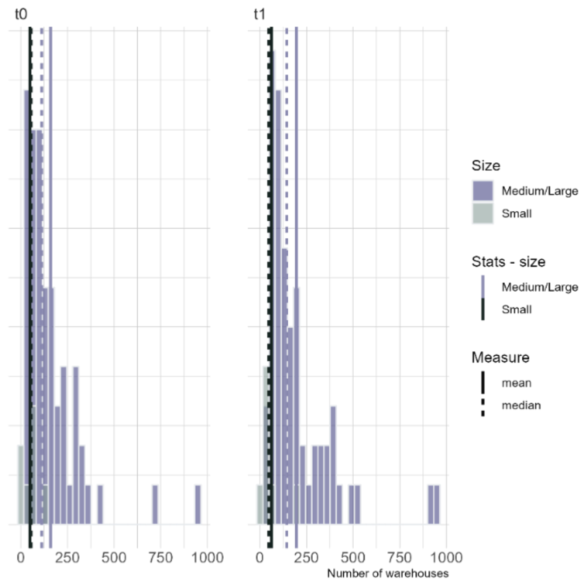


Figure 14: Histograms for the number of warehouses in different categories of metros and time – H1

A **complementary** statistical analysis was performed for each variable based on the size of the metropolitan area. The dataset was categorized into three distinct groups according to the size of the population: (i) small metropolitan areas (population of less than 1 million inhabitants); (ii) medium metropolitan areas (population between 1 million and 5 million inhabitants); (iii) large metropolitan areas (population exceeding 5 million inhabitants). As presented in the table below (table 11b), the number of warehouses at t1 tends to increase compared to t0 for all size categories. Additionally, the standard deviation at t1 is generally higher than at t0, indicating more variability in the number of warehouses. Large regions have the highest number of warehouses at both t0 and t1, followed by the medium and small regions. This result is consistent with H1 (There are more warehouses/pop in large and medium metropolitan regions than in smaller ones).

Table 11b: Central tendency and dispersion measures for the number of warehouses in relation to the size of the metropolitan areas

Statistics	Number of warehouses					
	Size: Small metropolitan areas		Size: Medium metropolitan areas		Size: Large metropolitan areas	
	T0	T1	T0	T1	T0	T1
Count	7	7	48	48	23	23
Mean	49	62.1	154.8	393.5	921	1332.3

Std	42.6	66.1	384.5	1546.3	1812.2	2011.3
Min	6	9	18	22	93	93
25%	18.5	31.5	52.5	71.5	220.5	308
50%	54	48	86.5	98	305	415
75%	57	54	130	157.75	651	1307.5
Max	132	207	2673	10553	8401	8766

The **number of warehouses per million inhabitants** (table 11c) follows the same trend as the number of warehouses presented previously, however, the highest number of warehouses per million inhabitants is located in medium size metropolitan areas followed closely by large metro areas.

Table 11c: Central tendency and dispersion measures for the number of warehouses per million inhabitants in relation to the size of the metropolitan areas

Statistics	**Number of warehouses per million inhabitants**					
	Size: Small metropolitan areas		Size: Medium metropolitan areas		Size: Large metropolitan areas	
	T0	T1	T0	T1	T0	T1
Count	7	7	46	48	23	23
Mean	95.3	101.6	145.6	258.9	131.9	150.2
Std	77	77.4	326.75	776.2	227	223.3
Min	17	23	5	5	10	6
25%	30.5	42.5	45.5	45	30.5	47.5
50%	65	61	60	64	63	80
75%	162	164.5	134.75	130.5	101.5	123

As for the **number of warehouses per 1000 km²** (table 11d), the same tendencies for the number of warehouses are observed.

Table 11c: Central tendency and dispersion measures for the number of warehouses per million inhabitants in relation to the size of the metropolitan areas

Statistics	Number of warehouses per 1000 km^2					
	Size: Small metropolitan areas		Size: Medium metropolitan areas		Size: Large metropolitan areas	
	T0	T1	T0	T1	T0	T1
Count	7	7	46	48	23	23
Mean	14.4	18	36.5	134.5	3708.5	12367
Std	17.3	21.8	153.4	674.1	17271.3	58669.3
Min	1	2	1	2	3	6
25%	2.5	3.5	6	6.75	10.5	16
50%	5	8	7.5	9.5	29	42
75%	24	26.5	14	18	79	170
Max	42	56	1046	4588	82933	281500

3.2.3. H2: There are more warehouses in global hub metropolitan regions (or 'gateways') than in regular ones

The variables considered to analyze hypothesis H2 are presented in Table 12.

Table 12: Variables considered to explore hypothesis H2

Variable Name	Description
metro	The name of the metropolitan area.
gateway	If the metropolitan region is a global hub city or gateway.
number_ware_t0	The number of warehouses in the metropolitan area at the start of the period covered by the dataset.
number_ware_t1	The number of warehouses in the metropolitan area at the end of the period covered by the dataset.

To perform this investigation, we:

(i) categorized the metropolitan areas into two groups based on their gateway characteristic: yes or no;

(ii) calculated the number of warehouses in each of these groups;

(iii) created a contingency table showing each group's average number of warehouses;

(iv) performed an outlier treatment to clean the data.

We must highlight that we withdrew two metropolitan areas from the sample since the data for Brussels and Cali did not present the number of warehouses in t0. We also determined the outliers for the dataset according to the interquartile range method, described in section 2.2.1, and excluded the metropolitan areas of **Shenzhen, Chongqing, Sao Paulo, Cape Town, eThekwini, Gauteng, and Seoul** (upper outliers) from the sample. Following the criteria for identifying outliers, **New York and Paris all** were considered outliers. Nevertheless, we did include these metropolitan areas in the clean dataset for this analysis. The average number of warehouses for the remaining sample (68 metros) is presented in Table 13.

As detailed in section 2.2, we have explored the differences in dependent variables between t0 and t1 and the difference in dependent variables regarding the categories. The results of the two approaches are presented in Table 14.

Table 13: Average number of warehouses, metro classification, and timeframe – H2

Data	Time	The average number of warehouses	Gateway	
			Yes	No
Complete	t0	374	347	438
	t1	518	541	466
Without outliers	t0	148	183	76
	t1	183	228	89

Table 14: Statistical tests and results – H2

Objective	Test	p-value	Interpretation
Dependent variables x timeframes	Wilcoxon Signed-Rank Test	1.284e-08 (complete data) 4.364e-07 (no outliers)	We reject the null hypothesis since the p-value is lower than 0.05. **We have sufficient evidence that the number of warehouses in t0 differs from t1.**
Dependent variables x categories	Mann-Whitney U test	1.778e-07 (complete data) 1.751e-07 (no outliers)	We reject the null hypothesis since the p-value is lower than 0.05. **We have sufficient evidence that the number of warehouses in gateway metros differs from non-gateway ones.**

In Table 14, we can verify that both tests indicate that we can reject the null hypothesis. Therefore, regarding time, we can state that the **average number of warehouses in the first year differs from that in the last year**. This information can also be verified in Figure 15, where the median and the distribution of metros considering the number of warehouses, differ. This figure was generated for the data without the aforementioned metropolitan areas as outliers.

Considering the second test for the H2 hypothesis, we can state that **the number of warehouses in gateway metros is higher than in non-gateway ones**, at a significance level of 5%. In Figure 16, we can notice the differences between the average and the median number of warehouses for both categories of metros, confirming H2.

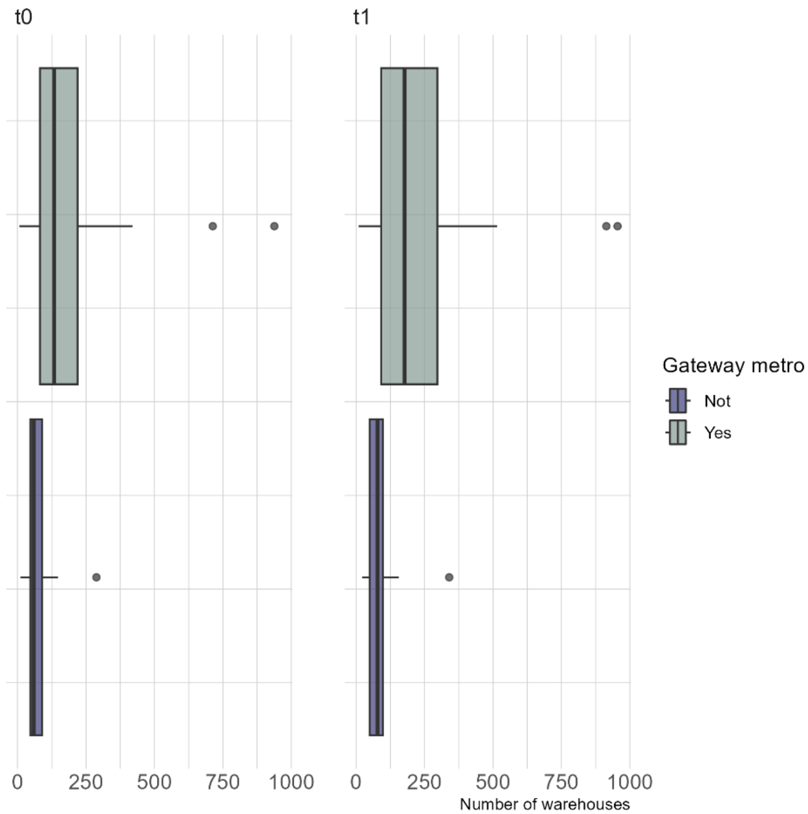


Figure 15: Boxplot for the number of warehouses in different categories of metros and time – H2

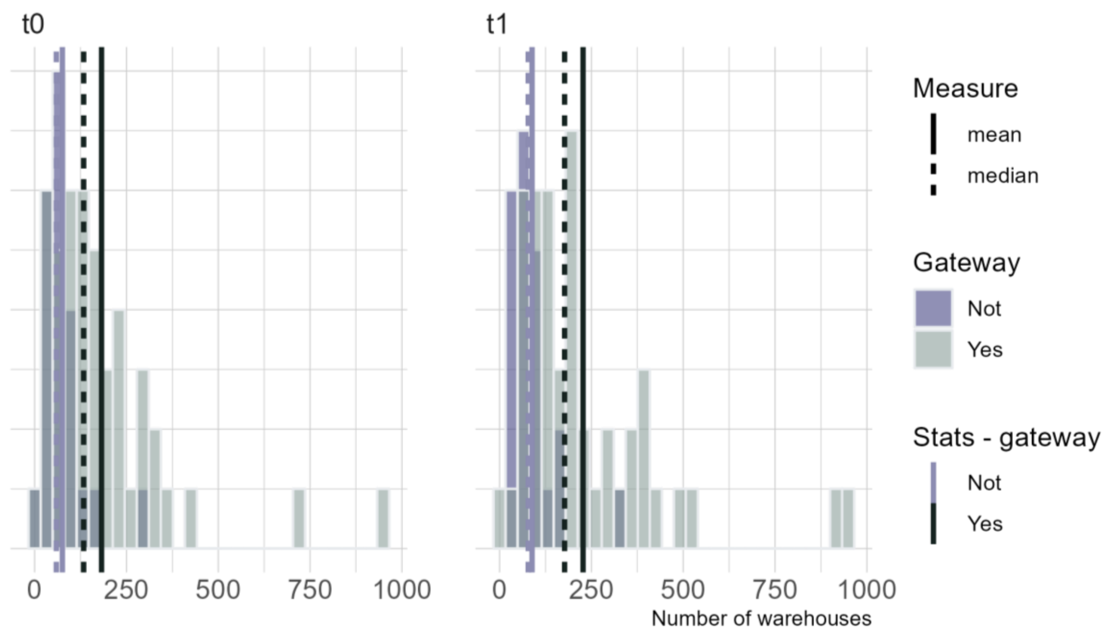


Figure 16: Histograms for the number of warehouses in different categories of metros and time – H2

3.2.4. H3: There are more warehouses in metropolitan regions that belong to megaregions than in "regular" ones

The variables considered to analyze hypothesis H3 are presented in Table 15.

Table 15: Variables considered to explore hypothesis H3

Variable Name	Description
metro	The name of the metropolitan area.
mega_region	If the metropolitan region is part of a mega-region.
number_ware_t0	The number of warehouses in the metropolitan area at the start of the period covered by the dataset.
number_ware_t1	The number of warehouses in the metropolitan area at the end of the period covered by the dataset.

To perform this investigation, we:

(i) categorized the metropolitan areas into two groups based on their location (belonging to a mega-region or not): yes or no;
(ii) calculated the number of warehouses in each of these groups;
(iii) created a contingency table showing each group's average number of warehouses;
(iv) performed an outlier treatment to clean the data.

The same process for outlier treatment was performed to clean the dataset for H2 analysis; the average number of warehouses for the remaining sample (68 metros) is presented in Table 16.

Table 16: Average number of warehouses, metro classification, and timeframe – H3

Data	Time	The average number of warehouses	Megaregion	
			Yes	No
Complete	t0	374	230	832
	t1	518	299	1210
Without outliers	t0	148	163	92
	t1	183	196	131

As detailed in section 2.2, we have explored the differences in dependent variables between t0 and t1 and the difference in dependent variables regarding the categories. The results of the two approaches are presented in Table 17.

Table 17: Statistical tests and results – H3

Objective	Test	p-value	Interpretation
Dependent variables x timeframes	Wilcoxon Signed-Rank Test	1.284e-08 (complete data) 4.364e-07	We reject the null hypothesis since the p-value is lower than 0.05. **We have sufficient evidence that the number of warehouses in t0 differs from t1.**

		(no outliers)	
Dependent variables x categories	Mann-Whitney U test	0.3812 (complete data) 0.002743 (no outliers)	We cannot reject the null hypothesis since the complete data's p-value is greater than 0.05. In this case, we do not have sufficient evidence to say that the number of warehouses in metros located in mega-regions differs from those that are not. On the other hand, we reject the null hypothesis since the p-value is lower than 0.05. In this case, **we have sufficient evidence that the number of warehouses in metros located in mega-regions differs from those that are not.**

In Table 17, we can verify that, if we consider the data without the abovementioned metros (outliers), both tests indicate that we can reject the null hypothesis. Therefore, regarding time, we can state that the **average number of warehouses in the first year differs from that in the last year**. This information can also be verified in Figure 17, where the median and the distribution of metros considering the number of warehouses, differ.

Considering the second test for the H3 hypothesis, we can state that **the number of warehouses in metro areas located in megaregions is higher than in the others**, at a significance level of 5%. In Figure 18, we can notice the differences between the average and the median number of warehouses for both categories of metros, confirming H3.

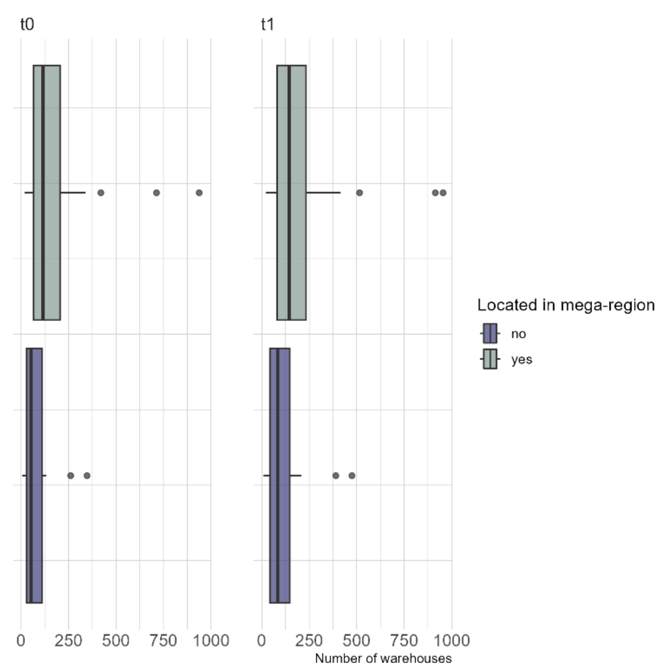


Figure 17: Boxplot for the number of warehouses in different categories of metros and time – H3

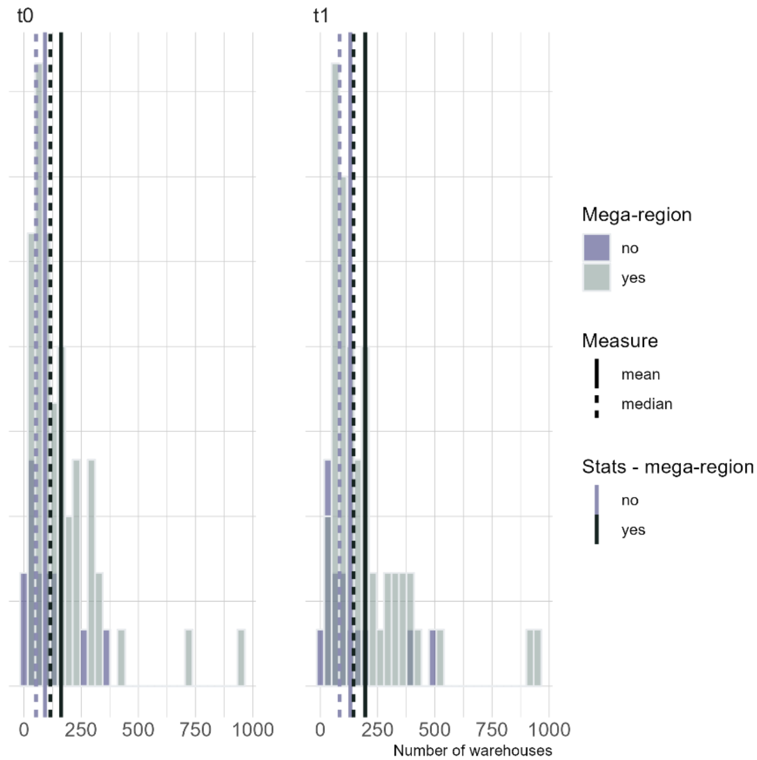


Figure 18: Histograms for the number of warehouses in different categories of metros and time – H3

3.2.5. H4: The increase in the number of warehouses over time is larger in medium and large metropolitan areas than in smaller ones.

The variables considered to analyze hypothesis H4 are presented in Table 18.

Table 18: Variables considered to explore hypothesis H4

Variable Name	Description
metro	The name of the metropolitan area.
size	The size of the metropolitan area (small, medium, or large).
number_ware_t0	The dataset covers the number of warehouses in the metropolitan area at the start of the period.
number_ware_t1	The number of warehouses in the metropolitan area at the end of the period covered by the dataset.

To perform this investigation, we:

(i) categorized the metropolitan areas into two groups based on their size (small or medium/large metros;

(ii) calculated the increase in the number of warehouses for all the data;

(iii) created a contingency table showing each group's average % increase in the number of warehouses;

(iv) performed an outlier treatment to clean the data.

We must highlight that we withdrew two metropolitan areas from the sample since the data for Brussels and Cali did not present the number of warehouses in t0. We also determined the outliers for the dataset considering the percentual increase in the number of warehouses and according to the interquartile range method, described in section 2.2.1. We excluded the metropolitan areas of **Chongqing, Sao Paulo, Belo Horizonte, Phoenix, Seoul** (upper outliers) from the sample. Following the criteria for identifying outliers, **Atlanta** and **Calgary** were considered outliers. Nevertheless, we did include these metropolitan areas in the clean dataset for this analysis.

In the case of this hypothesis, it is essential to highlight that we do not explore differences in time since the dependent variable is the increase in the number of warehouses. Table 19 shows the average increase in the number of warehouses according to metro size.

Table 19: Average increase in the number of warehouses, metro classification – H4

Data	**Size**	
	Small	**Medium/Large**
Complete	35%	59%
Without outliers	35%	26%

As detailed in section 2.2, we have explored the differences in the dependent variable (increase in number of warehouses) for small and medium/large metropolitan areas. The results are presented in Table 20.

Table 20: Statistical test and results – H4

Objective	**Test**	**p-value**	**Interpretation**
Dependent variables x categories	Mann-Whitney U test	0.9709 (complete data) 0.7026 (no outliers)	We cannot reject the null hypothesis since the p-values are greater than 0.05. In this case, **we do not have sufficient evidence to say that the increase in the number of warehouses in small metros differs from the medium/large ones**.

In Table 20, we can verify that if we consider the data without the abovementioned metros (outliers) the Mann-Whitney U test indicates that we cannot reject the null hypothesis. We can state that **the average % increase in the number of warehouses in small metro areas is not different from that in medium and large ones**, at a significance level of 5%. Figure 20 show that the median difference is more significant between samples, but even though the median for small metros lies outside the box for medium/large ones, the opposite is not valid, showing that differences are less likely. Also, the averages present more similar values (considering the dispersion of the data) but result from different data ranges and skewness. These differences in data structure with close central tendency measures do not let us state that there are statistically significant differences between the groups regarding these statistics.

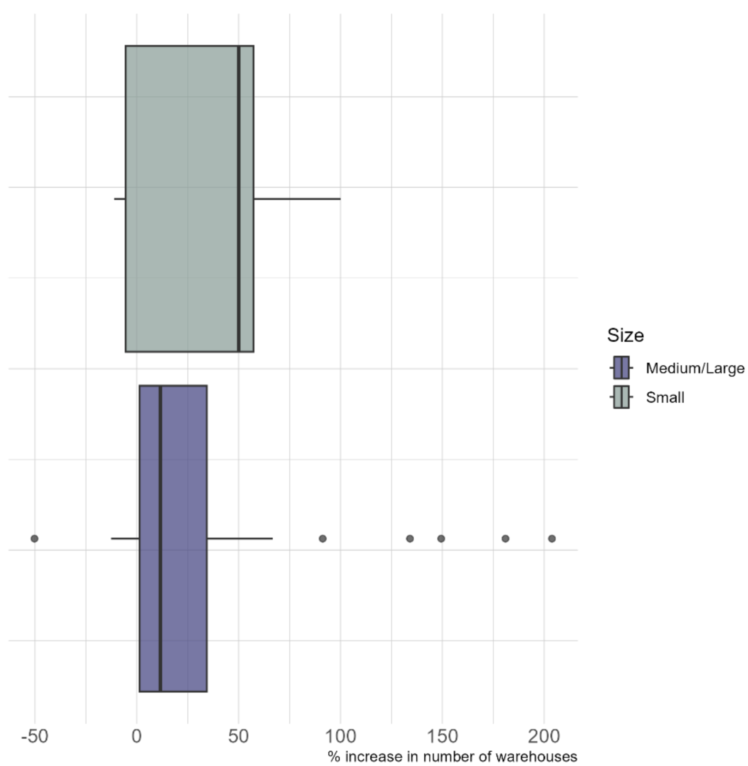


Figure 19: Boxplot for the increase in the number of warehouses in different categories of metros – H4

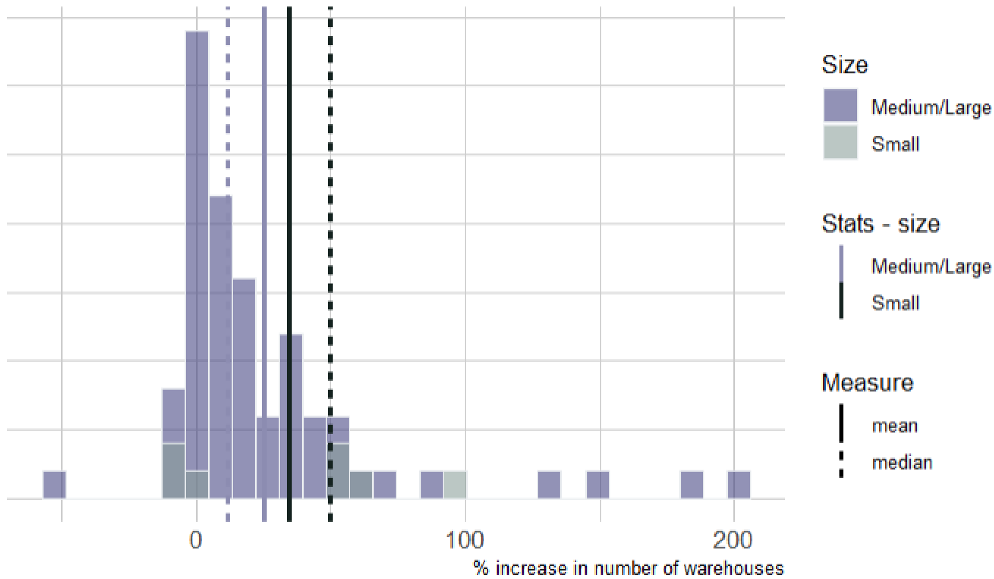


Figure 20: Histogram for the increase in the number of warehouses in different categories of metros – H4

3.2.6. H5: The increase in the number of logistics facilities over time is positively related to the importance of the role of global logistics hub (or Gateways) played by an urban area

The variables considered to analyze hypothesis H5 are presented in Table 21.

Table 21: Variables considered to explore hypothesis H5

Variable Name	Description
metro	The name of the metropolitan area.
gateway	If the metropolitan region is a global hub city or gateway.
number_ware_t0	The number of warehouses in the metropolitan area at the start of the period covered by the dataset.
number_ware_t1	The number of warehouses in the metropolitan area at the end of the period covered by the dataset.

To perform this investigation, we:

(i) categorized the metropolitan areas into two groups based on their position (gateway cities or not);

(ii) calculated the increase in the number of warehouses for all the data;

(iii) created a contingency table showing each group's average percentual increase in the number of warehouses.

(iv) performed an outlier treatment to clean the data.

We determined the outliers for the dataset considering the percentual increase in the number of warehouses and according to the interquartile range method, as performed for hypothesis H4. Table 22 shows the average increase in the number of warehouses according to metro classification.

Table 22: Average percentual increase in the number of warehouses, metro classification – H5

Data	Gateway	
	Yes	**No**
Complete	71%	26%
Without outliers	32%	16%

As detailed in section 2.2, we have explored the differences in the dependent variable (percentual increase in the number of warehouses) for gateway and non-gateway metropolitan areas. The results are presented in Table 23.

Table 23: Statistical test and results – H5

Objective	Test	p-value	Interpretation
Dependent variables x categories	Mann-Whitney U test	0.08273 (complete data) 0.1 (no outliers)	We cannot reject the null hypothesis since the p-values are greater than 0.05. **In this case, we do not have sufficient evidence to say that the % increase in the number of warehouses in gateway metros differs from the ones that are not.**

In Table 23, we can verify that if we consider the data without the abovementioned metros (outliers) the Mann-Whitney U test indicates that we cannot reject the null hypothesis. We can state that **the average % increase in the number of warehouses in gateway metros is not different from that in non-gateway ones**, at a significance level of 5%. Figure 22 show that the medians for gateway and non-gateway metros lie inside the other group box, indicating that differences are not likely. Also, the averages present more similar values (considering the dispersion of the data) but result from different data ranges and skewness. These differences in data structure with close central tendency measures do not let us state that there are statistically significant differences between the groups regarding these statistics.

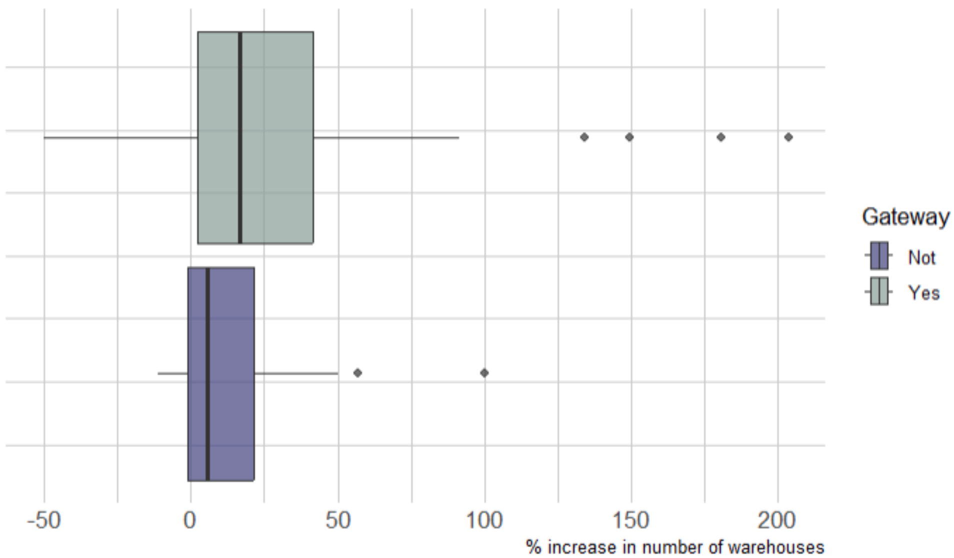


Figure 21: Boxplot for the % increase in the number of warehouses in different categories of metros – H5

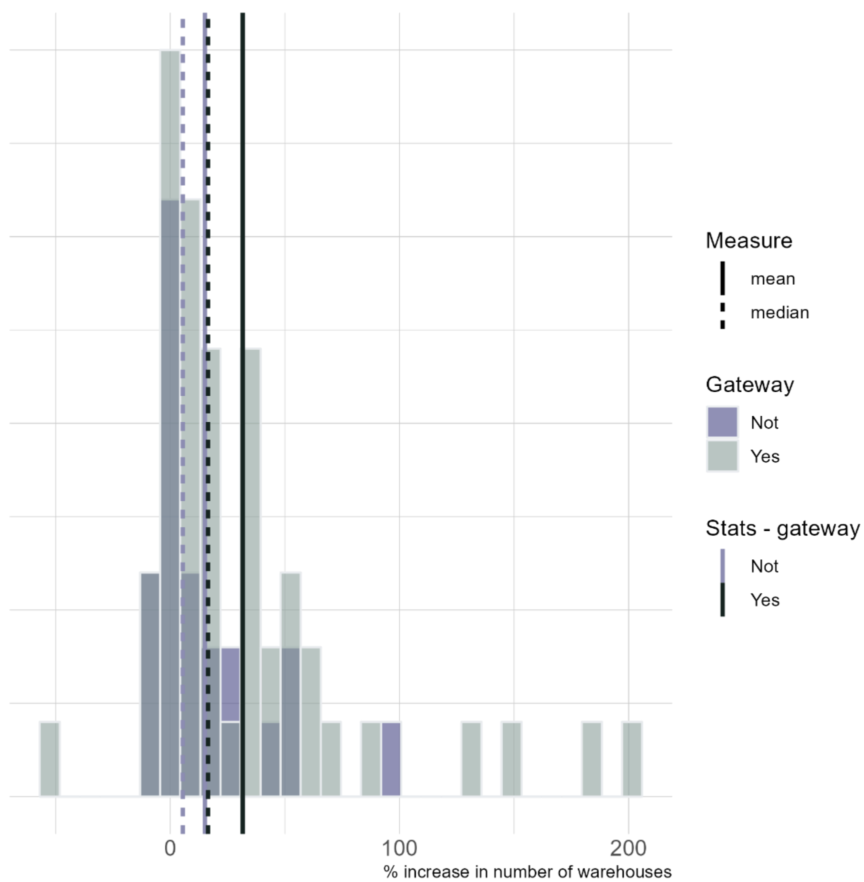


Figure 22: Histogram for the % increase in the number of warehouses in different categories of metros – H5

3.2.7. H6: Logistics sprawl is positively related to the differential in land/rent values for logistics land uses between suburban and central areas in an urban region

For this analysis, we increment the meta-analysis performed by the Chair's team (Dablanc et al., 2020) to compare the spatial patterns of warehouses and respective rent prices practiced by real estate agents in different cities around the world concerning the urban structure. We explored the relationship between the evolution in the number and location of logistics facilities over time and the differential warehouse prices in activity hubs and peripheral activity zones.

For this, we presented a methodological approach to address the logistics real estate market concerning the spatial structure of warehouse locations in worldwide metropolitan areas. The data was obtained in structured statistics datasets and warehouse real estate websites. We proposed a typology of the urban regions for determining the differential warehouse rent prices, namely *Activity Hubs* and *Peripheral Activity Zones*. This classification was based on an *Urban Activity Index*. Figure 23 shows the classification performed for Paris (region Ile-de-France).

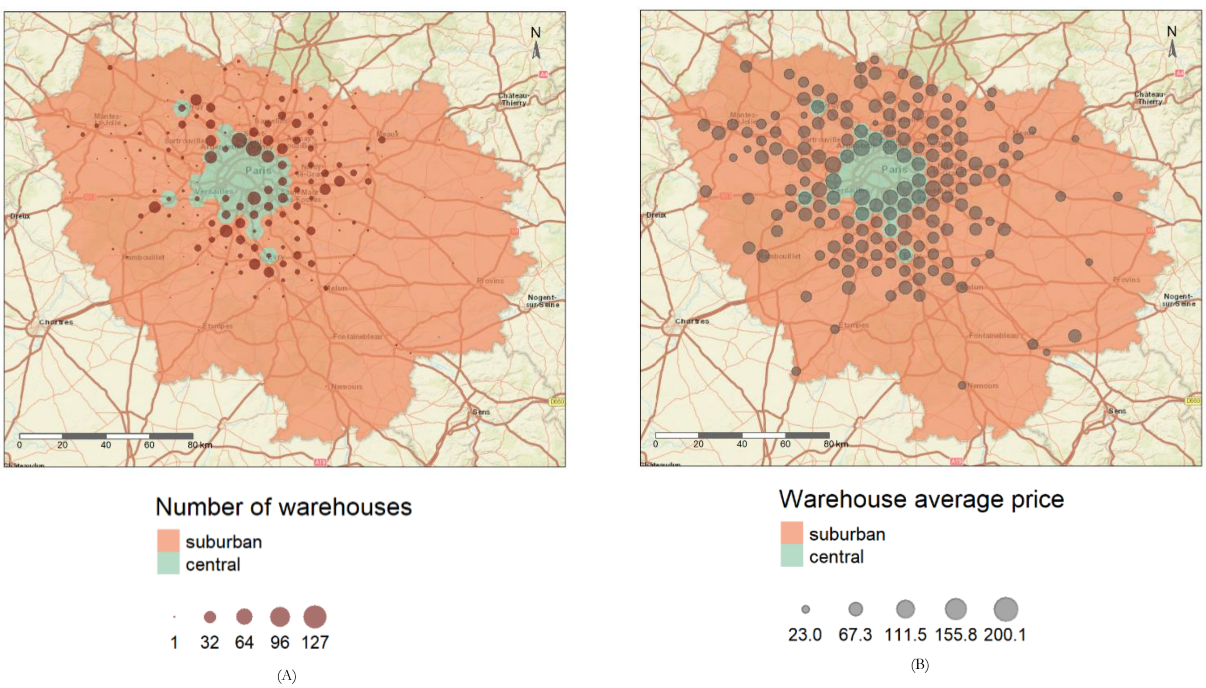


Figure 23: Representation of the number of warehouses and the average rent price in each hexagon for Paris (Ile-de-France region)

After the dataset and the classification of urban areas were concluded, we analyzed the relationship between differential warehouse rent prices (considering the classification of urban areas) and the yearly logistics sprawl by categorizing the data and using tests Chi-square to explore this relationship statistically.

Figure 24 presents the warehouse average rent prices for each metropolitan area. Figure 25 represents the average warehouse rent prices classified according to the location within the metropolitan area – differential rent price for AH and PAZ.

Figure 26 represents the proportional warehouse differential (ratio between AH/PAZ) areas. Figure 27 illustrates the average distance to the gravity center for t0 and t1 for each metropolitan region, and Figure 28, represents the yearly logistics sprawl for each metro area.

We observed that the average rent prices statistically depend on the location of warehouses in the observed metropolitan areas. Also, considering all the investigated metropolitan regions, we identify that the relationship between the differential warehouse prices and the yearly logistics sprawl is not statistically significant and demands further investigation due to local differences. Figure 29 presents the differential classes and a scatterplot for DWP and YLS.

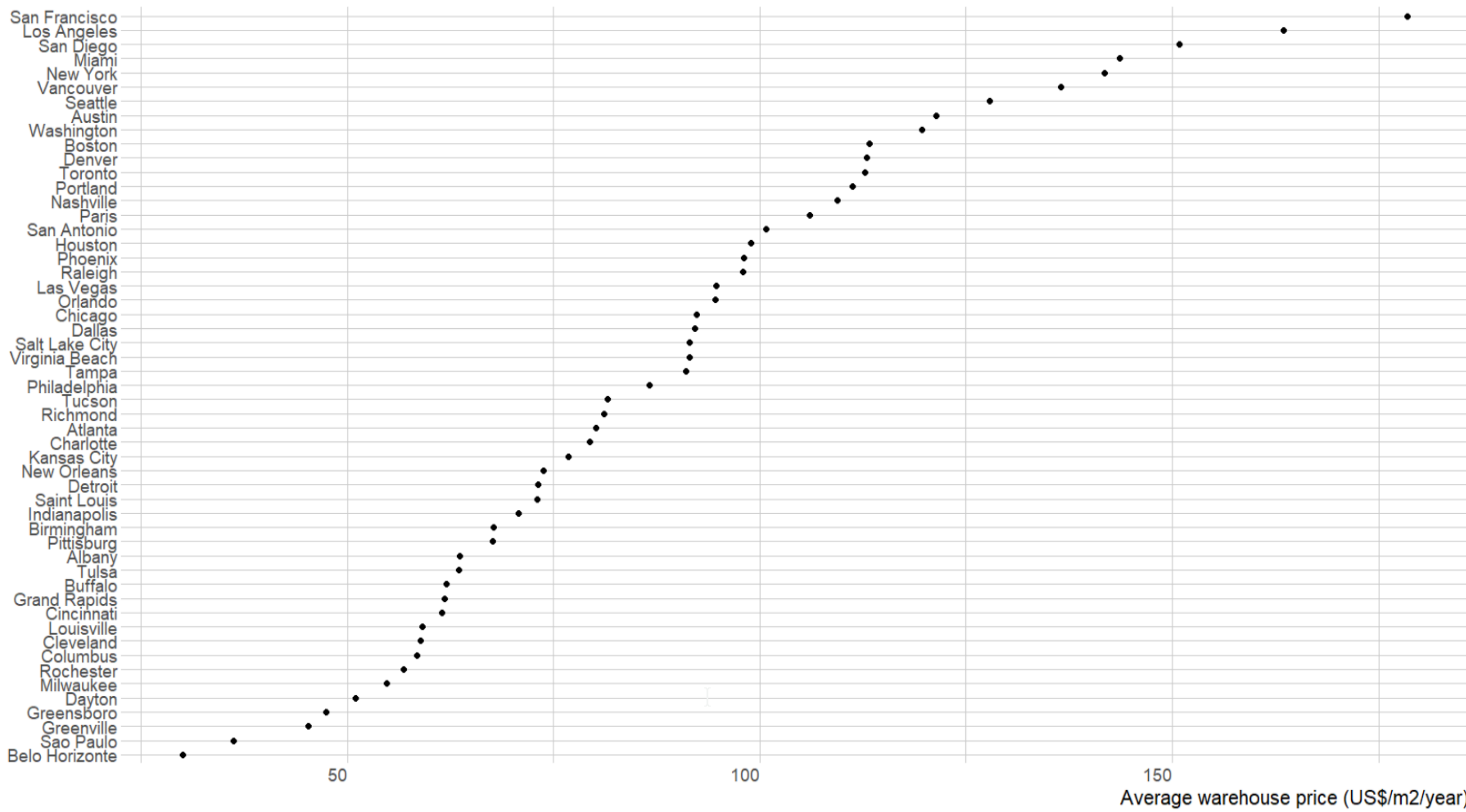


Figure 24: Representation of warehouse average rent prices for each metropolitan area of the dataset

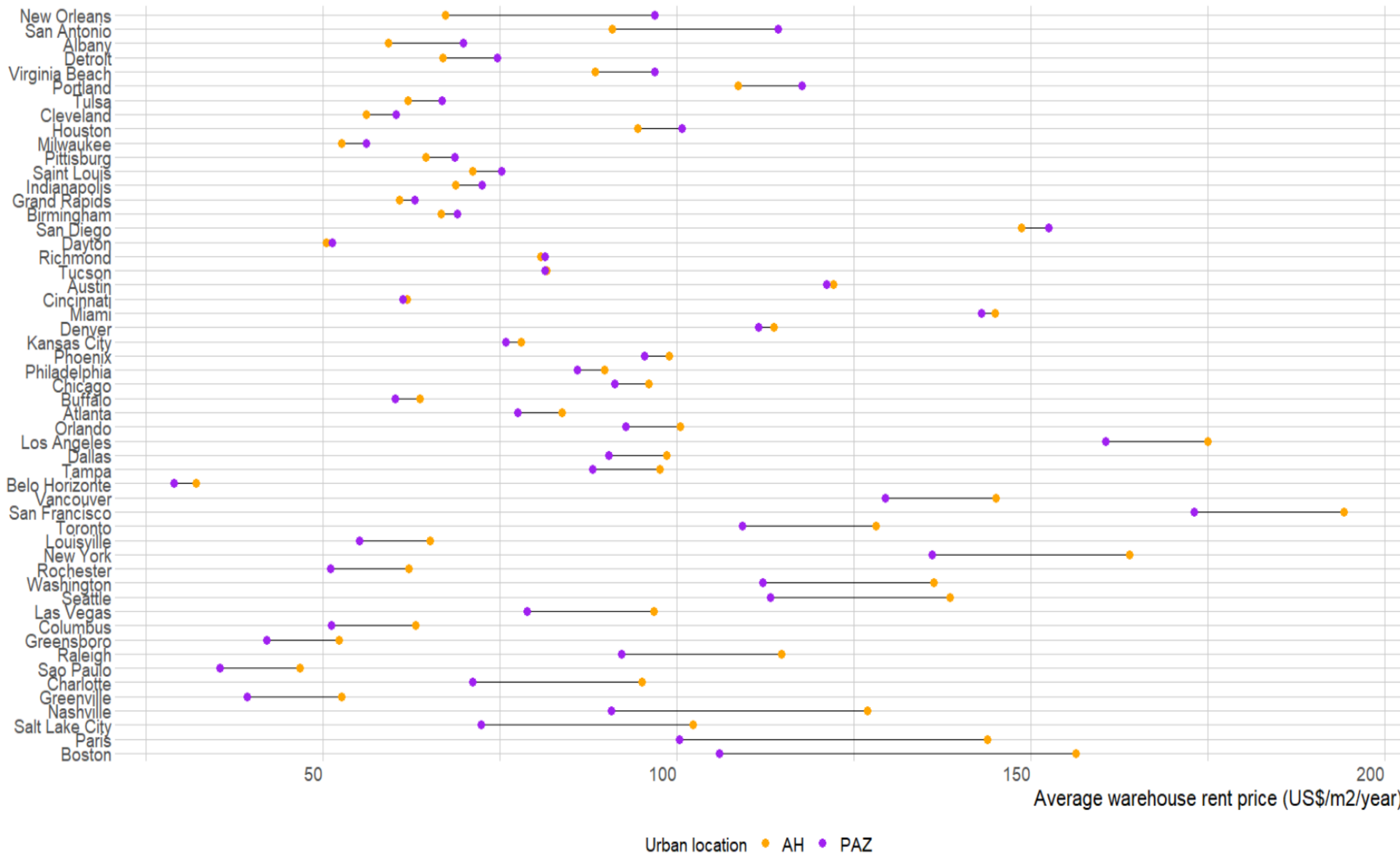


Figure 25: Representation of warehouse average rent prices for AH and PAZ for each metropolitan region of the dataset

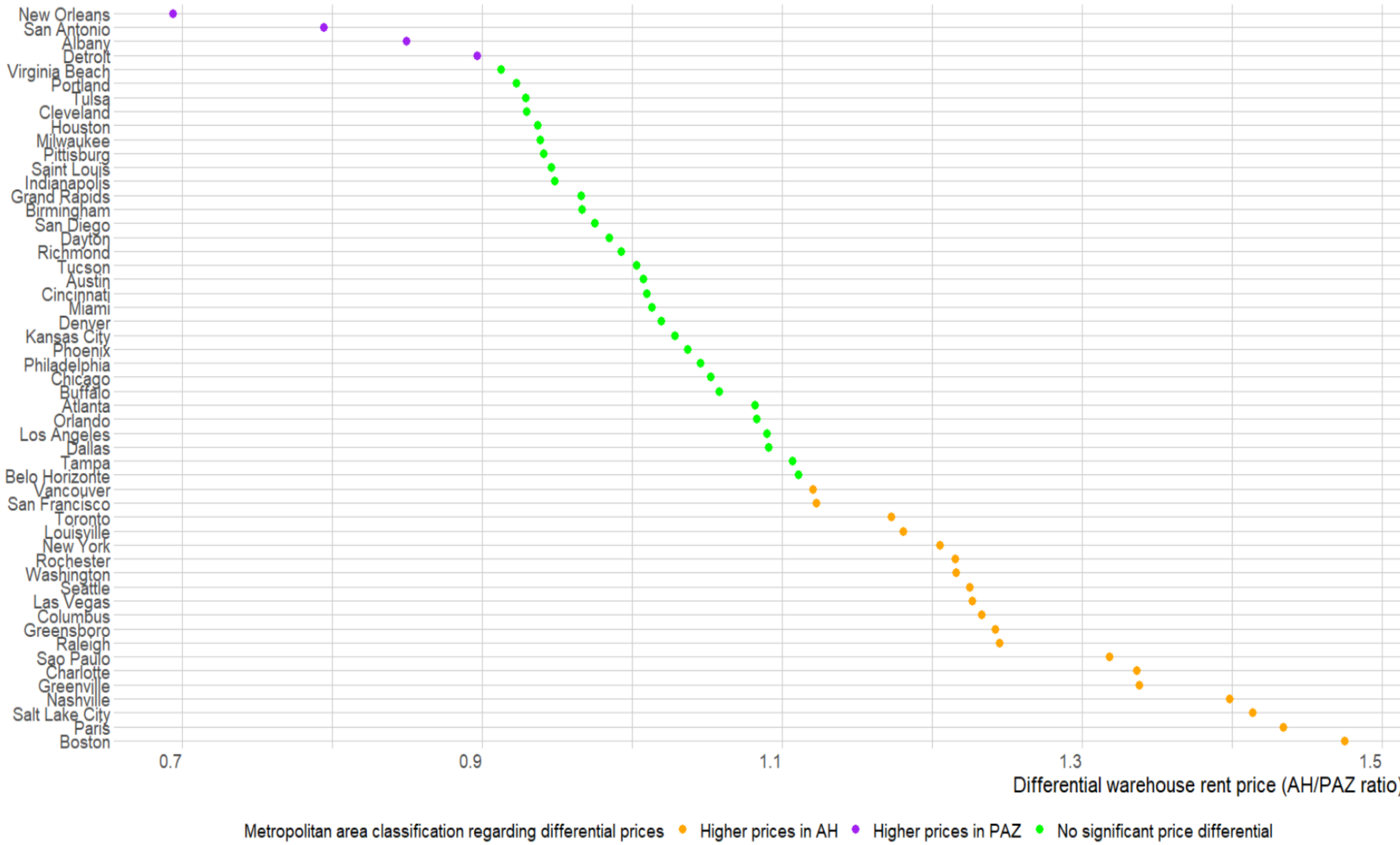


Figure 26: Representation of proportional rent prices differential for warehouses in each location for each metropolitan region of the dataset

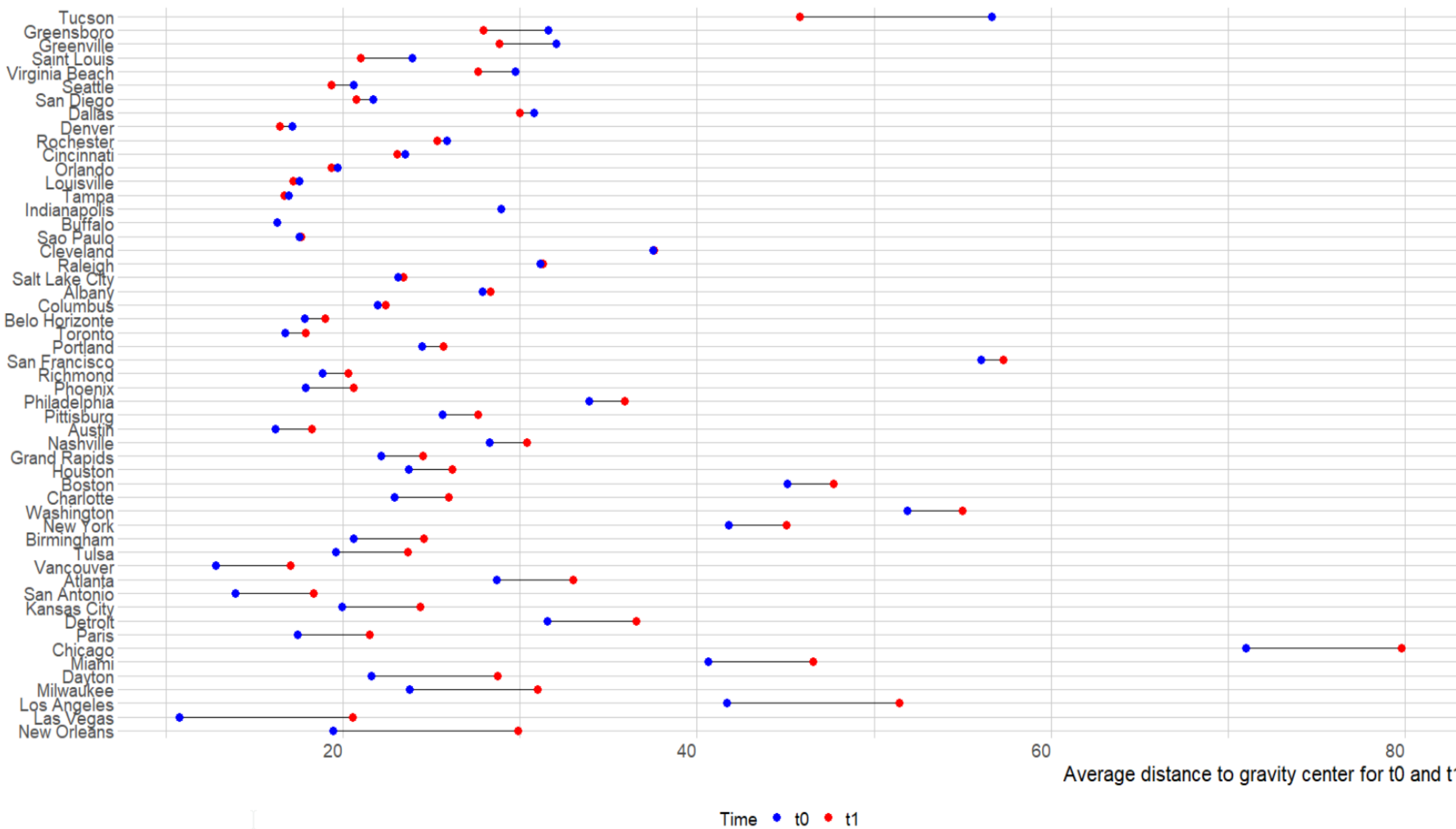


Figure 27: Representation of average distance to gravity center for t0 and t1, for each metropolitan region of the dataset

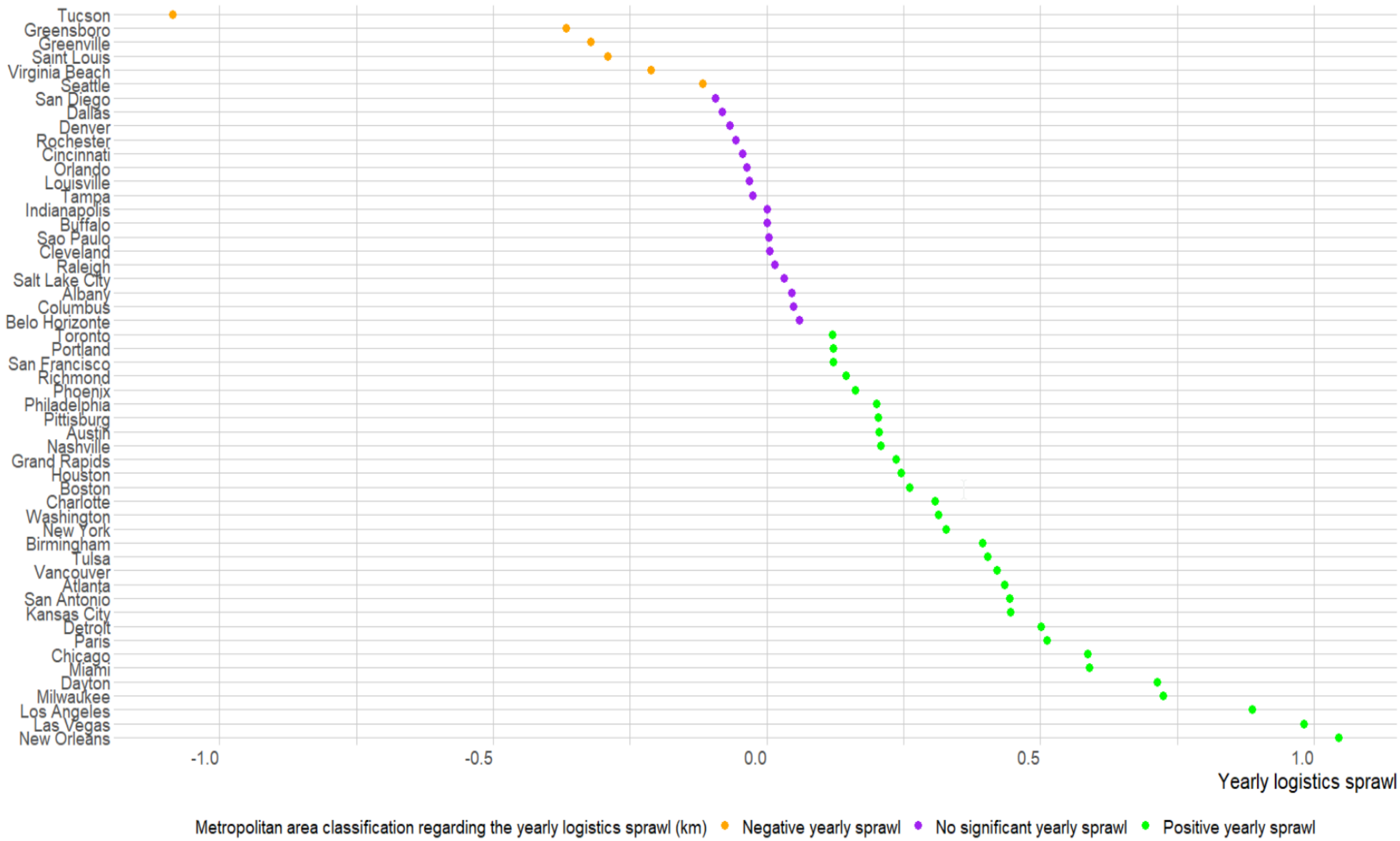


Figure 28: Representation of yearly logistics sprawl for each metropolitan area of the dataset

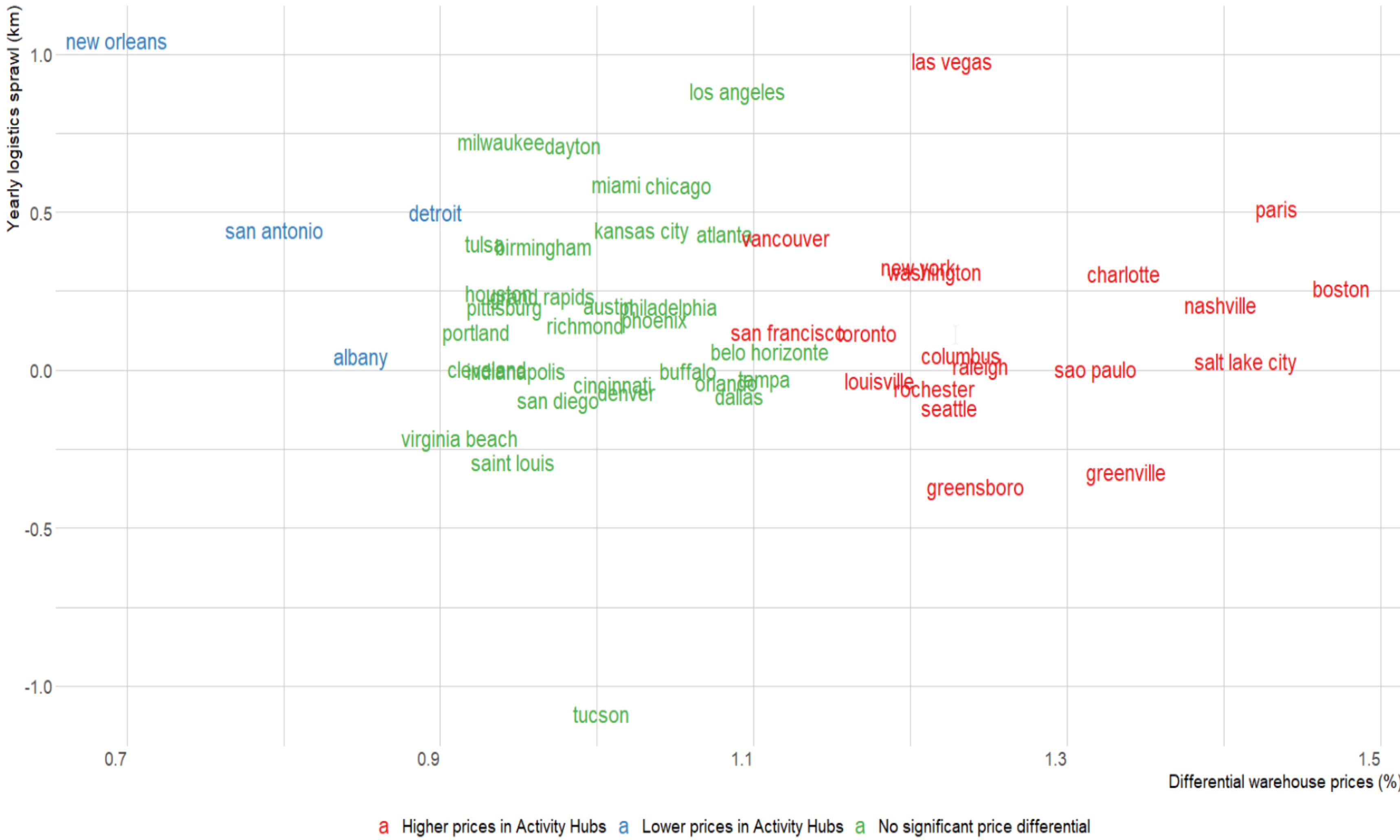


Figure 29: Differential classes and a scatterplot for DWP and YLS

Additional analysis of the spatial distribution of warehouses and the rental market for logistics real estate in the Tokyo metropolitan area (Gout, 2023).

This **study** was carried out as part of a research internship (from September 22 to December 19, 2022) at the Tokyo University of Marine Science and Technology, supervised by Takanori Sakai and funded by the Logistics City Chair (University Gustave Eiffel) under the supervision of Matthieu Schorung and Laetitia Dablanc. This research note presents a methodological proposal for acquiring and processing data from non-harmonized databases, using the Tokyo metropolitan area as a case study. Two objectives guided the writing of this research note: (i) to understand the spatial distribution of warehouses in the Tokyo metropolitan area; (ii) to obtain information on rents for logistics real estate in the Tokyo metropolitan area.

The main objective of the study is to estimate logistics real estate rents in the Tokyo metropolitan area. To achieve this, we created a multiple linear regression model. A multiple linear regression model works like a simple regression model, except that it uses several predictor variables. The objective is then to estimate the multiplier coefficients for each explanatory variable, which will enable us to obtain estimated values for the explained variable, in this case rent per m² for warehouses. Here is the model we have retained, after testing the different variables in the dataset:

monthly rent per m² ~ log(accessibility to industry) + accessibility to night-time population[1] + accessibility to consumption + distance-time to nearest port + ratio of commercial area + Tokyo Bay area (yes/no)

The model estimates rent per m² based on these 6 variables: (i) accessibility to industry, to the so-called "night-time" population (excluding commuting workers and visitors), to consumption; (ii) distance-time to nearest port (time needed to cover the distance between the warehouse and the nearest port); (iii) ommercial zone ratio (% of the area of the tile in which the warehouse is located belonging to the "commercial zone" zoning); (iv) Tokyo Bay zone (binary value (yes/no, 1/0) indicating whether the warehouse is located in the Tokyo Bay zone).

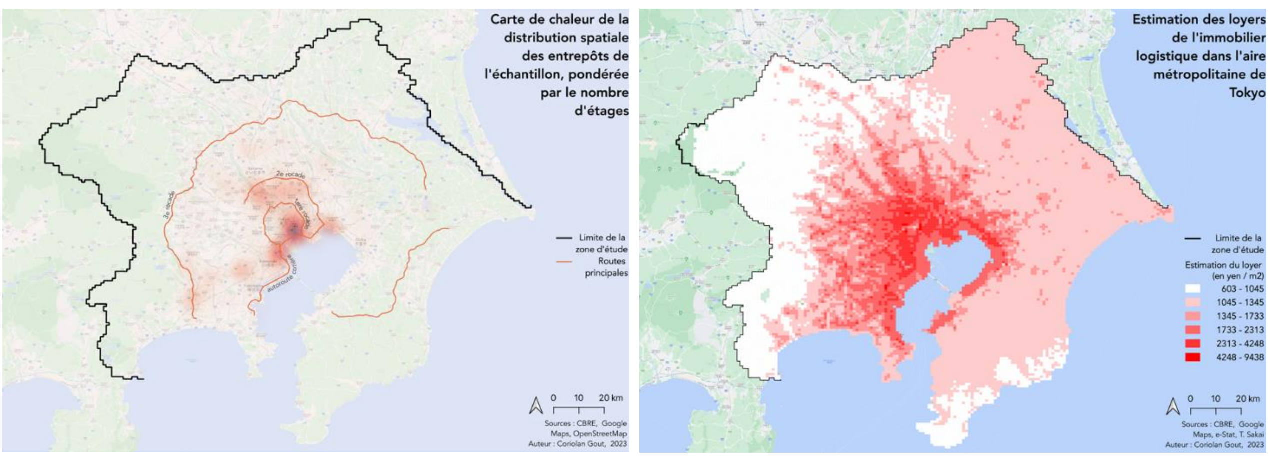
Warehouses are concentrated in specific areas (in order of importance): Tokyo harbor and surrounding area, Northern Tokyo between the first two ring roads; the bay area, from Kawasaki to Funabashi; the segment between the south-western end of the 3rd ring road and the port of Kawasaki. There is a high concentration of multi-storey warehouses in the Tokyo and Kawasaki ports. The highest rents are found near Tokyo Bay, particularly 4-5 km from the coast, the buffer zone for ports and coastal industries. Rents are very high in central

[1] The "night-time population" indicator refers to the resident population in a given geographical area, excluding commuters (who don't live in the area but work there) and temporary visitors.

Tokyo (over 2313 yen/m²/month, double the average). The western part of the study area, much less densely populated, offers very low rents.

On the scale of the study area, the variables with the greatest impact on rent per m² are, in order: distance-time to the nearest port, accessibility to the night-time population and accessibility to industry. Around Tokyo Bay, the variables with the greatest impact on rent per m² are, in order: accessibility to the night-time population, distance-time to the nearest port and accessibility to consumption. There is a **significant relationship between rent per m² and night-time accessibility, consumer accessibility and the presence of a warehouse in the Tokyo Bay area.**

We can identify three areas with high rents in Tokyo Bay: downtown Tokyo, around the bay (5 km from the coast) and along the main highways. We can observ a logistics sprawl phenomenon, concentrated around the 3rd ring road, and a concentration near the port areas, i.e. the center of the metro area. As the Port of Tokyo is located close to the city center, there is a high level of logistics activity. As a result, many warehouses are located close to the city center. Because land is so expensive, logistics real estate players prefer high-rise warehouses with multiple tenants.



(i) Spatial distribution map of sample warehouses, weighted by number of storeys (dataset of 4048 warehouses); (ii) Estimated rents for logistics real estate in the Tokyo metropolitan area (yen per sq.m per year) (Gout, 2023)

3.2.8. H7: Logistics sprawl is negatively related to the degree of regional logistics land-use control.

For this information, there is no sufficient data to allow the exploration of the hypothesis. This will require further analysis.

4. Conclusion

After a first phase of research from the Logistics City Chair (Dablanc et al., 2020), this report presents a methodological approach to further address the relationship between warehouses and some urban characteristics, including the logistics real estate market concerning the spatial structure of warehouse locations in 78 cases worldwide.

We provide a clean and comprehensive database for logistics facilities in large metropolitan areas based on gathering metadata and increment of researched secondary data regarding the urban characteristics of each metro area. Comparative results are presented concerning freight facility locational patterns based on various indicators identified by Dablanc et al. 2020. These results are synthetically presented in Table 24, based on hypotheses previously formulated by L. Dablanc (Dablanc et al., 2020).

From one perspective, when we compared the number of warehouses between the two periods in time, we identified different averages between them.

Considering the number of warehouses related to urban characteristics, we can realize that the average number of warehouses in small metros is lower than in medium/large ones. We also observed that the increase in the number of logistics facilities over time is positively related to the importance of the role of a global logistics hub (or gateways) played by an urban area. The location of the metropolitan regions in mega-regions impacts the number of warehouses, which are higher in these metros than in those not in these mega-regions.

From another perspective, considering the dynamics of warehouse placement, we did not find differences regarding the increase in the number of warehouses in small or medium/large metros or gateway and non-gateway ones.

Finally, when we consider the relationship between logistics sprawl and the differential in rent values of warehouses between central and suburban areas, we observe that the average rent prices statistically depend on the location of warehouses in the observed metropolitan regions. However, the relationship between the differential warehouse prices (central-suburban) and the yearly logistics sprawl is not statistically significant.

The findings lead us to recommend further investigation exploring local differences to include more specific information and determining subgroups according to these characteristics to understand the relationships between urban elements, warehouse location, real estate practices, and logistics sprawl.

Table 24: Summary of the main results

<table>
<tr><th>Hypotheses (Dablanc et al., 2020)</th><th>Independent variable</th><th>Dependent variable</th><th>Wilcoxon Signed-Rank Test</th><th>Mann-Whitney U test*</th></tr>
<tr><td>H1</td><td>Size (small or medium/large)</td><td>The average number of warehouses</td><td rowspan="3">We have sufficient evidence to infer that the average number of warehouses in the first year differs from that in the last year.</td><td>We have sufficient evidence to state that the average number of warehouses in small metro areas is lower than in medium/large ones.</td></tr>
<tr><td>H2</td><td>Gateway (yes or no)</td><td>The average number of warehouses</td><td>We have sufficient evidence to state that the number of warehouses in gateway metros is higher than in non-gateway ones.</td></tr>
<tr><td>H3</td><td>Megaregion (yes or no)</td><td>The average number of warehouses</td><td>We have sufficient evidence that the number of warehouses in metro areas located in mega-regions is higher than those that are not.</td></tr>
<tr><td>H4</td><td>Size (small or medium/large)</td><td>The average increase in the number of warehouses</td><td>-</td><td>We do not have sufficient evidence to say that the increase in the number of warehouses in small metros differs from the medium/large ones.</td></tr>
<tr><td>H5</td><td>Gateway (yes or no)</td><td>The average increase in the number of warehouses</td><td>-</td><td>We do not have sufficient evidence to say that the % increase in the number of warehouses in gateway metros differs from the ones that are not.</td></tr>
<tr><td>H6</td><td>Yearly logistics sprawl</td><td>Differential warehouse prices between central and suburban areas</td><td>-</td><td>*chi-square test
We do not have sufficient evidence to say that the yearly logistics sprawl is positively related to the differential warehouse prices.</td></tr>
</table>

For future studies, we recommend:

- Replicate the method to analyze differential location prices (Oliveira et al. (2022)) for metropolitan areas in the Global South.
- Investigate Asian metropolitan areas and South America metro areas to understand if there are differences in the urban structure and other characteristics compared to the other metro areas.

- To explore the Brazilian metropolitan areas to identify differences, especially considering the increase in the number of warehouses between periods.
- To refine the analysis of logistics sprawl considering warehouse characteristics, such as size, operation, and type of WH (for example, parcel and express couriers).
- To explore clusters of metropolitan areas grouped by urban characteristics to investigate the hypotheses considering the sub-groups of metros.
- To perform specific research on H7, exploring land use control, and regional and local policies.

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Appendix A. Metanalysis : metro areas studied in the selected papers of the metanalysis.

Andriankaja, D.	**Le desserrement logistique, quelle responsabilite dans l'augmentation des emissions de CO2 des activites de messagerie?**	**2014**	**[Phdthesis]. University of Paris-East.**	**Paris**
Dablanc, L., Ogilvie, S., & Goodchild, A.	Logistics Sprawl: Differential Warehousing Development Patterns in Los Angeles, California, and Seattle, Washington.	2014	Transportation Research Record: Journal of the Transportation Research Board, 2410(1), 105–112.	**Los Angeles, Seattle**
Dablanc, L., & Ross, C.	Atlanta: A mega logistics center in the Piedmont Atlantic Megaregion (PAM).	2012	Journal of Transport Geography, 24, 432–442.	**Atlanta**
Daraviña, P. A. C., & Suescún, J. P. B.	Logistic sprawl and polarization in Colombian urban areas.	2016	Proceedings WCTR.	**Colombia metro areas**
Dubie, M., Kuo, K. C., Giron-Valderrama, G., & Goodchild, A.	An evaluation of logistics sprawl in Chicago and Phoenix.	2020	Journal of Transport Geography, 88, 102298.	**Chicago, Phoenix**
Guerin, L., Vieira, J. G. V., de Oliveira, R., de Oliveira, L., Vieira, H. E. de M., & Dablanc, L.	The geography of warehouses in the São Paulo Metropolitan Region and contributing factors to this spatial distribution.	2021	Journal of Transport Geography, 91, 102976	**Sao Paulo**
Heitz, A., & Dablanc, L.	Logistics Spatial Patterns in Paris: Rise of Paris Basin as Logistics Megaregion	2015	Transportation Research Record: Journal of the Transportation Research Board, 2477(1), 76–84.	**Paris**
Heitz, A., Dablanc, L., Olsson, J., Sanchez-Diaz,	Spatial patterns of logistics facilities in Gothenburg, Sweden.	2020	Journal of Transport Geography, 88, 102191.	**Gothenburg**

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Heitz, A., Dablanc, L., & Tavasszy, L. A.	**Logistics sprawl in monocentric and polycentric metropolitan areas: The cases of Paris, France, and the Randstad, the Netherlands.**	**2017**	**Region, 4(1), 93.**	**Paris, Randstad (Netherlands)**
Kang, Sanggyun.	Exploring the contextual factors behind various phases in logistics sprawl: The case of Seoul Metropolitan Area, South Korea.	2022	Journal of Transport Geography.	**Seoul**
Kang, Sanggyun	Relative logistics sprawl: Measuring changes in the relative distribution from warehouses to logistics businesses and the general population.	2020	Journal of Transport Geography 83, 102636.	**US metro areas**
Klauenberg, J., Elsner, L. A., & Knischewski, C.	Dynamics of the spatial distribution of hubs in groupage networks – The case of Berlin.	2018	Journal of Transport Geography, May 2017, 102280.	**Berlin**
Li, G., Sun, W., Yuan, Q., & Liu, S.	Planning versus the market: Logistics establishments and logistics parks in Chongqing, China.	2020	Journal of Transport Geography, 82, 102599.	**Chongqing**
Oliveira, L., Santos, O., Oliveira, R., & Nóbrega, R.	Is the Location of Warehouses Changing in the Belo Horizonte Metropolitan Area (Brazil)? A Logistics Sprawl Analysis in a Latin American Context.	2018	Urban Science, 2(2), 43.	**Belo Horizonte**
Strale, M.	Logistics sprawl in the Brussels metropolitan area: Toward a socio-geographic typology.	2020	Journal of Transport Geography, 88, 102372.	**Brussels**
Trent, N. M., & Joubert, J. W.	Logistics sprawl and the change in freight transport activity: A comparison of three measurement methodologies.	2022	Journal of Transport Geography, 101, 103350.	**South African metro areas**
Woudsma, C., & Jakubicek, P.	Logistics land use patterns in metropolitan Canada.	2020	Journal of Transport	**Canada metro areas**

			Geography, 88, 102381.	
Woudsma, C., Jakubicek, P., & Dablanc, L.	Logistics sprawl in North America: Methodological issues and a case study in toronto.	2016	Transportation Research Procedia, 12, 474–488.	**Toronto**
Xiao, Z.	Remarking urban logistics space: E-tailing and supply chain revolution in the case of Shenzhen, China	2017	[Phdthesis]. The University of Hong Kong.	**Shenzhen**
Yuan, Q., & Zhu, J.	Logistics sprawl in Chinese metropolises: Evidence from Wuhan.	2019	Journal of Transport Geography, 74, 242–252.	**Wuhan**

Appendix B. Updated dataset on warehouses and logistics sprawl.

#	metro	years_data	number_ware_t0	number_ware_t1	log_sprawl_measure
70	albany	10	54	48	0.45
1	atlanta	10	132	401	4.34
66	austin	10	38	50	2.04
2	belo horizonte	20	44	156	1.19
3	berlin	20	18	22	3.97
67	birmingham	10	47	51	3.94
4	bogota	6	347	475	0.56
5	bordeaux	42	11	22	5.60
35	boston	10	290	294	2.61
6	brussels	30	NA	10553	2.50
65	buffalo	10	57	57	0,00
7	calgary	10	21	59	3.50
8	cali	3	NA	27	0.50
75	cape town	4	3899	4349	1.73
54	charlotte	10	124	145	3.07
9	chicago	15	217	415	8.80
10	chongqing	15	401	3490	16.00
51	cincinnati	10	112	122	-0.43
41	cleveland	10	148	150	0.05
50	columbus	10	208	195	0.48
37	dallas	10	338	402	-0.82
71	dayton	10	54	49	7.13
45	denver	10	118	147	-0.68
39	detroit	10	196	210	5.02
76	eThekwini	4	2673	2733	-0.25
11	flevoland	6	60	59	NA
77	gauteng	4	8401	8766	1.52
12	gothenburg mea	14	132	207	4.20
13	gothenburg vgc	14	261	390	2.70
64	grand rapids	10	62	72	2.37
62	greensboro	10	88	88	-3.67
68	greenville	10	101	97	-3.20
14	halifax	10	6	9	1.10
40	houston	10	221	298	2.46
52	indianapolis	10	121	171	0.00
49	kansas city	10	159	153	4.46
58	las vegas	10	51	80	9.80
15	los angeles	11	220	515	9.75
63	louisville	10	81	89	-0.32

38	miami	10	193	235	5.91
53	milwaukee	10	101	98	7.24
16	montreal	10	79	70	0.30
60	nashville	10	116	121	2.08
59	new orleans	10	77	83	10.44
32	new york	10	938	914	3.27
17	noord holland	6	318	278	NA
48	orlando	10	75	91	-0.37
18	paris all	8	713	955	4.10
19	paris parcels	36	93	93	11.80
36	philadelphia	10	288	340	2.01
20	phoenix	17	41	183	2.74
44	pittsburgh	10	92	98	2.03
46	portland	10	160	163	1.21
61	raleigh	10	76	77	0.14
24	randstad	6	589	583	NA
72	richmond	10	58	87	1.45
69	rochester	10	45	48	-0.56
55	salt lake city	10	88	117	0.31
56	san antonio	10	47	67	4.44
42	san diego	10	84	86	-0.93
34	san francisco	10	305	349	1.22
21	sao paulo	25	228	2066	0.10
22	seattle	11	85	212	-1.29
78	seoul	27	984	3340	4.10
23	shenzhen	4	1430	1660	1.23
43	st louis	10	148	144	-2.91
47	tampa	10	63	79	-0.26
25	tokyo	23	420	209	4.20
26	toronto ggh	10	217	350	9.50
27	toronto gta	10	165	228	1.20
74	tucson	10	33	55	-10.86
73	tulsa	10	39	37	4.02
28	utrecht	6	43	61	NA
29	vancouver	10	135	134	4.20
57	virginia beach	10	90	98	-2.12
33	washington dc	10	285	318	3.14
30	winnipeg	10	26	41	0.00
31	zuid holland	6	168	185	NA

Appendix C. Complete database of the Logistics City Chair.

#	Name of studied metro area	Size of studied metro area (km2)	Number of municipalities	Type of metropolitan area	Type of land use control	Gateway	Megaregion	Name of Megaregion	Type of city	Focused Study	Interviews	Name of warehouse data source	Time period studied for logistics sprawl analysis	Number of years analysed	First year of study (T=0)	T=0 Population (millions)	T=0 Population density (inhabitants/km2)	T=0 Number of warehouses	T=0 Number of warehouses per million people	T=0 Number of warehouses per 1000 km2	T=0 Average size of warehouses (m2)
1	Atlanta metro area	21694	16	Polycentric or rather polycentric	Local	Yes	Yes	Char-Lanta	Medium	Not	Yes	NAICS 493	1998 - 2008	10	1998	4,30	198,3	132	31	6	NA
2	Belo Horizonte	9460	34	Monocentric or rather monocentric	Local	Yes	Not	Not	Medium	Not	Not	MRC + CB	1995 - 2015	20	1995	0,78	82,6	44	56	5	NA
3	Berlin	3778	51	Polycentric or rather polycentric	Local	Yes	Yes	Berlin	Medium	Yes	Yes	Own (focused study)	1994 - 2014	20	1994	3,41	903,4	18	5	5	NA
4	Bogotá	1775,96	1	Monocentric or rather monocentric	Local	Yes	Not	Not	Large	Not	Not	Land use data from Capital District of Bogota	2005 - 2011	6	2005	8,11	4564,6	347	43	195	709
5	Bordeaux MA	5613	27	Monocentric or rather monocentric	Local	Not	Not	Not	Small	Yes	Yes	Own collection from yellow pages	1970 - 2012	42	1970	0,58	104,0	11	19	2	NA
6	Brussels	2300	19	Monocentric or rather monocentric	Local	Yes	Yes	Am-Brus-Twerp	Medium	Not	Not	Belgian Statistical Office	1982 - 2012	30	1982	1,66	722,6	NA	#VALEUR!	#VALEUR!	NA
7	Calgary	825	0	Monocentric or rather monocentric	Not indicated	Yes	Not	Not	Medium	Not	Not	Enhaced Points of Interest (EPOI) from DMTI Spatial + NAICS 493	2002 - 2012	10	2002	1,02	1237,6	21	21	25	NA
8	Cali	798		Monocentric or rather monocentric	Local	Not	Not	Not	Medium	Not	Not	Chamber of Commerce	2005 - 2008	3	2005	2,08	2610,5	NA	#VALEUR!	#VALEUR!	NA
9	Chicago	24814,7	10	Monocentric or rather monocentric	Local	Yes	Yes	Chi-Pitts	Large	Not	Not	NAICS 493	1998 - 2013	15	1998	7,69	310,0	217	28	9	NA
10	Chongqing	82403	458	Polycentric or rather polycentric	Not indicated	Yes	Not	Not	Large	Yes	Not	National Enterprise Credit Information Publicity System + Transportation, Warehousing and Postal (TWP) China classification	2001 - 2016	15	2001	17,80	216,0	401	23	5	NA
11	Flevoland	1419	NA	Monocentric or rather monocentric	Not indicated	Not	Yes	Am-Brus-Twerp	Small	Not	Yes	NACE 52.10 + Lisa Database	2007 - 2013	6	2007	0,37	261,9	60	161	42	NA
12	Gothenburg (MIA)	3695	13	Monocentric or rather monocentric	Metropolitan	Yes	Not	Not	Small	Not	Yes	NACE 52.10 + Statistics Sweden database (SBC)	2000 - 2014	14	2000	0,81	219,2	132	163	36	NA
13	Gothenburg (VGC region)	22750	48	Monocentric or rather monocentric	Not indicated	Yes	Not	Not	Medium	Not	Yes	NACE 52.10 + Statistics Sweden database (SBC)	2000 - 2014	14	2000	1,50	65,7	261	175	11	NA
14	Halifax	5496	NA	Monocentric or rather monocentric	Not indicated	Yes	Not	Not	Small	Not	Not	Enhaced Points of Interest (EPOI) from DMTI Spatial + NAICS 493	2002 - 2012	10	2002	0,36	65,4	6	17	1	NA
15	Los Angeles	87490	NA	Polycentric or rather polycentric	Local	Yes	Yes	SoCal	Large	Not	Not	NAICS 493	1998 - 2009	11	1998	3,72	42,5	220	59	3	NA
16	Montreal	4259	90	Monocentric or rather monocentric	Not indicated	Yes	Yes	Tor-Buff-Chester	Medium	Not	Not	Enhaced Points of Interest (EPOI) from DMTI Spatial + NAICS 493	2002 - 2012	10	2002	2,61	611,8	79	30	19	NA
17	Noord Holland (Amsterdam)	2670	NA	Monocentric or rather monocentric	Regional	Yes	Yes	Am-Brus-Twerp	Medium	Not	Yes	NACE 52.10 + Lisa Database	2007 - 2013	6	2007	2,61	979,1	318	122	119	NA
18	Paris (all WH) 2004 - 2012	12012	1300	Monocentric or rather monocentric	Local	Yes	Yes	Paris	Large	Not	Not	CLAP Local knowledge of the Productive Systems + NACE 52.1	2004 - 2012	8	2004	11,36	945,4	713	63	59	NA
19	Paris (parcel/express)	12012	1300	Monocentric or rather monocentric	Local	Yes	Yes	Paris	Large	Yes	Yes	Own collection from yellow pages	1974 - 2010	36	1974	9,49	789,7	93	10	8	NA
20	Phoenix	37813	NA	Monocentric or rather monocentric	Not indicated	Yes	Yes	Phoenix-Tucson	Medium	Not	Not	NAICS 493	1998 - 2015	17	1998	3,05	80,6	41	13	1	NA
21	São Paulo	7944	39	Polycentric or rather polycentric	Local	Yes	Yes	São Paulo	Large	Not	Not	São Paulo Commercial Registry	1992 - 2017	25	1992	15,08	1898,5	228	15	29	NA
22	Seattle	15209	NA	Polycentric or rather polycentric	Regional	Yes	Yes	Cascadia	Medium	Not	Not	NAICS 493	1998 - 2009	11	1998	2,95	193,8	85	29	6	NA
23	Shenzhen	1996,85	10	Polycentric or rather polycentric	Not indicated	Yes	Yes	Hong-Shen	Large	Not	Yes	Shenzhen Census (Urban Planning and Ressource comission)	2008 - 2012	4	2008	9,58	4798,9	1430	149	716	300>
24	The Randstad Region	8357	183	Polycentric or rather polycentric	Regional	Yes	Yes	Am-Brus-Twerp	Large	Not	Yes	NACE 52.10 + Lisa Database	2007 - 2013	6	2007	7,63	913,0	588	77	70	NA
25	Tokio (TMA)	13500	23	Polycentric or rather polycentric	Local	Yes	Yes	Greater Tokyo	Large	Not	Not	TMFS WH	1980 - 2003	23	1980	27,11	2007,9	420	15	31	400
26	Torono GGH (Greater Golden Horseshoe)	31561	40	Polycentric or rather polycentric	Regional	Yes	Yes	Tor-Buff-Chester	Large	Not	Not	NAICS 493	2002 - 2012	10	2002	7,57	239,7	217	29	7	NA
27	Torono GTA	5906	25	Monocentric or rather monocentric	Regional	Yes	Yes	Tor-Buff-Chester	Large	Not	Not	NAICS 493	2002 - 2012	10	2002	5,08	860,5	165	32	28	NA

#	Name of studied metro area	Last year of study (T=N)	T=N Population (millions)	T=N Population density (inhabitants/km2)	T=N Number of warehouses	T=N Number of warehouses per million people	T=N Number of warehouses per 1000 km2	T=N Average size of warehouses (m2)	Change in population over the years (millions)	T=0 Average distance of warehouses to centre of gravity (km)	T=N Average distance of warehouses to centre of gravity (km)	Change in average distance of WHs to centre of gravity (over the years) (km)	Logistic sprawl (km/year)	Change in number of WH over the years	% change in number of WH over the years	Change of warehouses per million people over the years	Logistic sprawl	Surfaces area data availability	Urban Rent Prices per year (EUR/m2)	Suburban Rent Prices per year (EUR/m2)	% of increase in rent price of suburban compared to urban rent	Increase in rent price of suburban compared to urban rent	Logistic Sprawl analysis
1	Atlanta metro area	2008	5,00	230,5	401	80	18	NA	0,7	28,6	33,0	4,3	0,43	269	204%	50	Yes	Not	48,05 €	40,49 €	19%	Yes	Logistic Sprawl <5km
2	Belo Horizonte	2015	5,00	528,5	156	31	17	NA	4,2	17,8	19	1,2	0,06	113	258%	-25	Yes	Not	54,47 €	46,20 €	18%	Yes	Logistic Sprawl <5km
3	Berlin	2014	4,34	1149,0	22	5	6	NA	0,9	11,72	15,7	4,0	0,20	4	22%	0	Yes	Not	63,50 €	58,80 €	8%	Yes	Logistic Sprawl <5km
4	Bogotá	2011	8,78	4943,7	475	54	267	712	0,7	4,941	5,506	0,6	0,09	128	37%	11	Yes	Yes	223,56 €	198,72 €	13%	Yes	Logistic Sprawl <5km
5	Bordeaux MA	2012	0,72	128,6	22	30	4	NA	0,1	1,3	6,9	5,6	0,13	11	100%	12	Yes	Not	45,04 €	43,00 €	5%	Yes	Logistic Sprawl 5km - 10 km
6	Brussels	2012	2,50	1087,0	10553	4221	4588	NA	0,8	18,7	21,2	2,5	0,08	#VALEUR!	#VALEUR!	#VALEUR!	Yes	Not	61,05 €	58,00 €	5%	Yes	Logistic Sprawl <5km
7	Calgary	2012	1,31	1587,9	59	45	72	NA	0,3	5,4	8,9	3,5	0,35	38	181%	24	Yes	Not	79,05 €	76,14 €	4%	Yes	Logistic Sprawl <5km
8	Cali	2008	2,12	2656,6	27	13	34	NA	0,04	2	2,5	0,5	0,17	#VALEUR!	#VALEUR!	#VALEUR!	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
9	Chicago	2013	7,30	294,2	415	57	17	NA	-0,4	71	79,8	8,8	0,59	198	91%	29	Yes	Not	60,16 €	49,12 €	22%	Yes	Logistic Sprawl 5km - 10 km
10	Chongqing	2016	30,00	364,1	3490	116	42	NA	12,2	17,9	33,9	16,0	1,07	3089	770%	94	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl >10km
11	Flevoland	2013	0,40	279,7	59	149	42	NA	0,0	NA	NA	3,3	0,55	-1	-2%	-13	Not	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
12	Gothenburg (MIA)	2014	0,97	263,3	207	213	56	NA	0,2	9,1	13,3	4,2	0,30	75	57%	50	Yes	Not	82,10 €	78,00 €	5%	Yes	Logistic Sprawl <5km
13	Gothenburg (VGC region)	2014	1,62	71,0	390	241	17	NA	0,1	79,3	82	2,7	0,19	129	49%	67	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
14	Halifax	2012	0,39	71,0	9	23	2	NA	0,0	3,6	4,7	1,1	0,11	3	50%	6	Yes	Not	126,62 €	122,35 €	3%	Yes	Logistic Sprawl <5km
15	Los Angeles	2009	18,00	205,7	515	29	6	NA	14,3	41,7	51,4	9,7	0,89	295	134%	-30	Yes	Not	139,50 €	101,14 €	38%	Yes	Logistic Sprawl 5km - 10 km
16	Montreal	2012	2,85	669,0	70	25	16	NA	0,2	8,8	9,1	0,3	0,03	-9	-11%	-6	Yes	Not	71,11 €	69,65 €	2%	Yes	Logistic Sprawl <5km
17	Noord Holland (Amsterdam)	2013	2,70	1011,2	278	103	104	NA	0,1	NA	NA	-2,0	-0,33	-40	-13%	-19	Not	Not	63,00 €	60,00 €	5%	Yes	Not Logistic Sprawl
18	Paris (all WH) 2004 - 2012	2012	11,90	990,7	955	80	80	NA	0,5	17,4	21,5	4,1	0,51	242	34%	17	Yes	Not	58,38 €	56,00 €	4%	Yes	Logistic Sprawl <5km
19	Paris (parcel/express)	2010	11,77	980,0	93	8	8	5000	2,3	6,3	18,1	11,8	0,33	0	0%	-2	Yes	Not	58,38 €	56,00 €	4%	Yes	Logistic Sprawl >10km
20	Phoenix	2015	4,20	111,1	183	44	5	NA	1,2	17,86	20,6	2,7	0,16	142	346%	30	Yes	Not	129,04 €	70,91 €	82%	Yes	Logistic Sprawl <5km
21	São Paulo	2017	21,60	2719,0	2066	96	260	NA	6,5	17,5	17,6	0,1	0,00	1838	806%	81	Not	Not	89,99 €	46,44 €	94%		Logistic Sprawl <5km
22	Seattle	2009	3,50	230,1	212	61	14	NA	0,6	20,599552	19,31208	-1,3	-0,12	127	149%	32	Not	Not	136,01 €	86,03 €	58%	Yes	Not Logistic Sprawl
23	Shenzhen	2012	12,00	6009,5	1660	138	831	300>	2,4	14,892	16,124	1,2	0,31	230	16%	-11	Yes	Yes	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
24	The Randstad Region	2013	7,10	849,6	583	82	70	NA	-0,5	NA	NA	0,0	0,00	-6	-1%	5	Not	Not	NA	NA	#VALEUR!	NA	Not Logistic Sprawl
25	Tokio (TMA)	2003	36,00	2666,7	209	6	15	400	8,9	26,5	30,7	4,2	0,18	-211	-50%	-10	Yes	Yes	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
26	Torono GGH (Greater Golden Horseshoe)	2012	8,46	268,2	350	41	11	NA	0,9	29,6	39,1	9,5	0,95	133	61%	13	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl 5km - 10 km
27	Torono GTA	2012	6,05	1025,1	228	38	39	NA	1,0	16,7	17,9	1,2	0,12	63	38%	5	Yes	Not	83,02 €	82,44 €	1%	Yes	Logistic Sprawl <5km

28	Utrecht	1450	NA	Monocentric or rather monocentric	Not indicated	Yes	Yes	Am-Brus-Twerp	Medium	Not	Yes	NACE 52.10 + Lisa Database	2007 - 2013	6	2007	1,22	842,9	43	35	30	NA	2013	1,20	827,6	61	51	42	NA	0,0	NA	NA	0,5	0,08	18	42%	16	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
29	Vancouver	2700	NA	Monocentric or rather monocentric	Not indicated	Yes	Yes	Cascadia	Medium	Not	Not	Enhaced Points of Interest (EPOI) from DMTI Spatial + NAICS 493	2002 - 2012	10	2002	2,22	823,9	135	61	50	NA	2012	2,59	959,6	134	52	50	NA	0,4	12,8	17	4,2	0,42	-1	-1%	-9	Yes	Not	181,83 €	120,32 €	51%	Yes	Logistic Sprawl <5km
30	Winnipeg	5306	18	Monocentric or rather monocentric	Local	Yes	Not	Not	Small	Not	Not	Enhaced Points of Interest (EPOI) from DMTI Spatial + NAICS 493	2002 - 2012	10	2002	0,62	117,1	26	42	5	NA	2012	0,67	125,7	41	61	8	NA	0,0	4,9	4,9	0,0	0,00	15	58%	20	Yes	Not	76,05 €	72,4626761	5%	Yes	Logistic Sprawl <5km
31	Zuid Holland (Rotterdam)	2818	NA	Monocentric or rather monocentric	Not indicated	Yes	Yes	Am-Brus-Twerp	Medium	Not	Yes	NACE 52.10 + Lisa Database	2007 - 2013	6	2007	3,42	1214,1	168	49	60	NA	2013	3,60	1277,5	185	51	66	NA	0,2	NA	NA	-1,0	-0,17	17	10%	2	Not	Not	68,12 €	65,00 €	5%	Yes	Not Logistic Sprawl
32	New York, United States	11880	11	Polycentric or rather polycentric	Local	Yes	Yes	Bos-Wash	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	20,78	1749,3	998	45	79	NA	2013	22,46	1890,7	914	41	77	NA	1,7	41,78	45,05	3,3	0,33	-24	-3%	-4	Yes	Not	109,76 €	85,73 €	28%	Yes	Logistic Sprawl <5km
33	Washington DC, United States	14412	7	Polycentric or rather polycentric	Local	Yes	Yes	Bos-Wash	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	7,71	534,7	285	37	20	NA	2013	8,75	606,9	318	36	22	NA	1,0	51,87	55,01	3,1	0,31	33	12%	-1	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
34	San Francisco, United States	6410	9	Polycentric or rather polycentric	Local	Yes	Yes	Nor-Cal	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	5,89	919,2	305	52	48	NA	2013	6,44	1004,5	349	54	54	NA	0,5	56,07	57,29	1,2	0,12	44	14%	2	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
35	Boston, United States	3680	8	Polycentric or rather polycentric	Local	Yes	Yes	Bos-Wash	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	6,84	1858,6	290	42	79	NA	2013	7,21	1960,3	294	41	80	NA	0,4	45,11	47,72	2,6	0,26	4	1%	-2	Yes	Not	196,27 €	152,58 €	29%	Yes	Logistic Sprawl <5km
36	Philadelphia, United States	13256	14	Polycentric or rather polycentric	Local	Not	Yes	Bos-Wash	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	6,16	464,6	288	47	22	NA	2013	6,46	487,3	340	53	26	NA	0,3	33,89	35,90	2,0	0,20	52	18%	6	Yes	Not	60,26 €	55,70 €	8%	Yes	Logistic Sprawl <5km
37	Dallas, United States	24059	12	Polycentric or rather polycentric	Local	Yes	Yes	Dal-Austin	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	5,59	232,3	338	60	14	NA	2013	6,84	284,2	402	59	17	NA	1,2	30,80	29,98	-0,8	-0,08	64	19%	-2	Not	Not	59,68 €	40,69 €	47%	Yes	Not Logistic Sprawl
38	Miami, United States	15890	107	Polycentric or rather polycentric	Local	Yes	Yes	So-Flo	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	5,64	354,8	193	34	12	NA	2013	6,30	396,4	235	37	15	NA	0,7	40,64	46,54	5,9	0,59	42	22%	3	Yes	Not	80,79 €	75,56 €	7%	Yes	Logistic Sprawl 5km - 10 km
39	Detroit, United States	15060	130	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	4,82	320,2	196	41	13	NA	2013	4,64	308,4	210	45	14	NA	-0,2	31,53	36,55	5,0	0,50	14	7%	5	Yes	Not	59,58 €	56,09 €	6%	Yes	Logistic Sprawl 5km - 10 km
40	Houston, United States	26061	9	Polycentric or rather polycentric	Local	Yes	Yes	Hou-Orleans	Large	Not	Not	NAICS 493	2003 - 2013	10	2003	5,08	194,8	221	44	8	NA	2013	6,31	241,9	298	47	11	NA	1,2	23,69	26,15	2,5	0,25	77	35%	4	Yes	Not	93,10 €	74,50 €	25%	Yes	Logistic Sprawl <5km
41	Cleveland, United States	10307	NA	Polycentric or rather polycentric	Local	Not	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	3,25	315,2	148	46	14	NA	2013	3,16	306,7	150	47	15	NA	-0,1	37,50	37,55	0,0	0,00	2	1%	2	Not	Not	36,81 €	35,84 €	3%	Yes	Not Logistic Sprawl
42	San Diego, United States	11720	18	Polycentric or rather polycentric	Local	Yes	Yes	So-Cal	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,93	250,1	84	29	7	NA	2013	3,22	274,6	86	27	7	NA	0,3	21,68	20,74	-0,9	-0,09	2	2%	-2	Not	Not	14,53 €	9,78 €	49%	Yes	Not Logistic Sprawl
43	St. Louis, United States	21910	NA	Polycentric or rather polycentric	Local	Yes	Yes	Tor-Buff-Chester	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,79	127,5	148	53	7	NA	2013	2,87	130,8	144	50	7	NA	0,1	23,91	21,00	-2,9	-0,29	-4	-3%	-3	Not	Not	42,43 €	41,46 €	2%	Yes	Not Logistic Sprawl
44	Pittsburgh, United States	13840	12	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,63	190,2	92	35	7	NA	2013	2,57	186,0	98	38	7	NA	-0,1	25,60	27,63	2,0	0,20	6	7%	3	Yes	Not	51,44 €	52,89 €	-3%	Not	Logistic Sprawl <5km
45	Denver, United States	17213	10	Polycentric or rather polycentric	Local	Yes	Yes	Denver-Boulder	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,30	133,7	118	51	7	NA	2013	2,70	156,6	147	55	9	NA	0,4	17,11	16,43	-0,7	-0,07	29	25%	3	Not	Not	75,95 €	57,74 €	32%	Yes	Not Logistic Sprawl
46	Portland, United States	17310	NA	Polycentric or rather polycentric	Local	Yes	Yes	Cascadia	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,40	138,8	160	67	9	NA	2013	2,57	148,7	163	63	9	NA	0,2	24,43	25,64	1,2	0,12	3	2%	-3	Yes	Not	68,59 €	75,56 €	-9%	Not	Logistic Sprawl <5km
47	Tampa, United States	6610	NA	Polycentric or rather polycentric	Local	Not	Yes	So-Flo	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,53	383,0	63	25	10	NA	2013	2,87	434,6	79	28	12	NA	0,3	16,91	16,66	-0,3	-0,03	16	25%	3	Not	Not	53,48 €	54,06 €	-1%	Not	Not Logistic Sprawl
48	Orlando, United States	10390	NA	Polycentric or rather polycentric	Local	Yes	Yes	So-Flo	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,27	218,6	75	33	7	NA	2013	2,87	275,9	91	32	9	NA	0,6	19,70	19,33	-0,4	-0,04	16	21%	-1	Not	Not	73,72 €	57,83 €	27%	Yes	Not Logistic Sprawl
49	Kansas City, United States	21940	12	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,90	86,8	159	83	7	NA	2013	2,05	93,6	153	75	7	NA	0,1	19,91	24,37	4,5	0,45	-6	-4%	-9	Yes	Not	63,26 €	40,01 €	58%	Yes	Logistic Sprawl <5km
50	Columbus, United States	8208	NA	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,83	222,5	208	114	25	NA	2013	2,03	247,5	195	96	24	NA	0,2	21,92	22,40	0,5	0,05	-13	-6%	-18	Yes	Not	38,94 €	33,42 €	17%	Yes	Logistic Sprawl <5km
51	Cincinnati, United States	12450	NA	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	2,08	166,9	112	54	9	NA	2013	2,15	172,9	122	57	10	NA	0,1	23,50	23,06	-0,4	-0,04	10	9%	3	Not	Not	73,14 €	59,48 €	23%	Yes	Not Logistic Sprawl
52	Indianapolis, United States	15614	11	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,71	109,7	121	71	8	NA	2013	2,07	132,4	171	83	11	NA	0,4	28,90	28,90	0,0	0,00	50	41%	12	Not	Not	66,94 €	42,24 €	58%	Yes	Not Logistic Sprawl
53	Milwaukee, United States	3781	4	Polycentric or rather polycentric	Local	Not	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,71	451,4	101	59	27	NA	2013	1,77	467,3	98	55	26	NA	0,1	23,74	30,98	7,2	0,72	-3	-3%	-4	Yes	Not	40,69 €	39,14 €	4%	Yes	Logistic Sprawl 5km - 10 km
54	Charlotte, United States	8280	10	Polycentric or rather polycentric	Local	Yes	Yes	Char-lanta	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,44	173,6	124	86	15	NA	2013	2,34	282,2	145	62	18	NA	0,9	22,90	25,97	3,1	0,31	21	17%	-24	Yes	Not	122,26 €	38,75 €	216%	Yes	Logistic Sprawl <5km
55	Salt Lake City, United States	20960	2	Polycentric or rather polycentric	Local	Yes	Yes	Denver-Boulder	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,41	67,4	88	62	4	NA	2013	1,70	81,3	117	69	6	NA	0,3	23,11	23,42	0,3	0,03	29	33%	6	Yes	Not	84,86 €	59,29 €	43%	Yes	Logistic Sprawl <5km
56	San Antonio, United States	1546	8	Polycentric or rather polycentric	Local	Not	Yes	Dal-Austin	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,82	1177,7	47	26	30	NA	2013	2,28	1474,6	67	29	43	NA	0,5	13,89	18,33	4,4	0,44	20	43%	4	Yes	Not	59,00 €	59,00 €	0%	Not	Logistic Sprawl <5km
57	Virginia Beach, United States	9660	15	Polycentric or rather polycentric	Local	Not	Not	NA	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,64	169,5	90	55	9	NA	2013	1,71	177,2	98	57	10	NA	0,1	29,72	27,60	-2,1	-0,21	8	9%	2	Not	Not	NA	NA	#VALEUR!	NA	Not Logistic Sprawl
58	Las Vegas, United States	20880	NA	Polycentric or rather polycentric	Local	Not	Not	NA	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,58	75,5	51	32	2	NA	2013	2,03	97,0	80	39	4	NA	0,4	10,73	20,54	9,8	0,98	29	57%	7	Yes	Not	106,95 €	77,89 €	37%	Yes	Logistic Sprawl 5km - 10 km
59	New Orleans, United States	9726	8	Polycentric or rather polycentric	Local	Yes	Yes	Hou-Orleans	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,42	146,1	77	54	8	NA	2013	1,37	140,9	83	61	9	NA	-0,1	19,44	29,89	10,4	1,04	6	8%	6	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl >10km
60	Nashville, United States	19380	6	Polycentric or rather polycentric	Local	Not	Not	NA	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,37	70,8	116	85	6	NA	2013	1,75	90,5	121	69	6	NA	0,4	28,29	30,37	2,1	0,21	5	4%	-16	Yes	Not	132,91 €	56,58 €	135%	Yes	Logistic Sprawl <5km
61	Raleigh, United States	11415	23	Polycentric or rather polycentric	Local	Not	Yes	Char-Lanta	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,33	116,6	76	57	7	NA	2013	1,75	153,3	77	44	7	NA	0,4	31,16	31,30	0,1	0,01	1	1%	-13	Not	Not	70,43 €	56,19 €	25%	Yes	Logistic Sprawl <5km
62	Greensboro, United States	10364	NA	Polycentric or rather polycentric	Local	Not	Not	NA	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,10	106,0	88	80	8	NA	2013	1,39	134,5	88	63	8	NA	0,3	31,58	27,91	-3,7	-0,37	0	0%	-17	Not	Not	NA	NA	#VALEUR!	NA	Not Logistic Sprawl
63	Louisville, United States	10711	NA	Polycentric or rather polycentric	Local	Yes	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,33	124,3	81	61	8	NA	2013	1,44	134,7	89	62	8	NA	0,1	17,51	17,19	-0,3	-0,03	8	10%	1	Not	Not	56,77 €	38,85 €	46%	Yes	Not Logistic Sprawl
64	Grand Rapids, United States	17610	4	Polycentric or rather polycentric	Local	Not	Yes	Chi-Pitts	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	0,94	53,1	62	66	4	NA	2013	1,18	67,2	72	61	4	NA	0,2	22,16	24,53	2,4	0,24	10	16%	-5	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
65	Buffalo, United States	4060	2	Polycentric or rather polycentric	Local	Yes	Yes	Tor-Buff-Chester	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,16	285,6	57	49	14	NA	2013	1,13	279,2	57	50	14	NA	0,0	16,29	16,29	0,0	0,00	0	0%	1	Not	Not	41,17 €	41,17 €	0%	Not	Not Logistic Sprawl
66	Austin, United States	11080	5	Polycentric or rather polycentric	Local	Yes	Yes	Dal-Austin	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,38	124,3	38	28	3	NA	2013	1,89	170,9	50	26	5	NA	0,5	16,17	18,22	2,0	0,20	12	32%	-1	Yes	Not	130,39 €	69,46 €	88%	Yes	Logistic Sprawl <5km
67	Birmingham, United States	13673	7	Polycentric or rather polycentric	Local	Not	Yes	Char-Lanta	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,15	84,3	47	41	3	NA	2013	1,23	90,2	51	41	4	NA	0,1	20,60	24,54	3,9	0,39	4	9%	1	Yes	Not	73,92 €	26,35 €	181%	Yes	Logistic Sprawl <5km
68	Greenville, United States	15980	10	Polycentric or rather polycentric	Local	Not	Yes	Char-lanta	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,01	63,3	101	100	6	NA	2013	1,17	73,3	97	83	6	NA	0,2	32,03	28,82	-3,2	-0,32	-4	-4%	-17	Not	Not	37,20 €	37,20 €	0%	Not	Not Logistic Sprawl
69	Rochester, United States	7600	6	Polycentric or rather polycentric	Local	Not	Yes	Tor-Buff-Chester	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,14	149,5	45	40	6	NA	2013	1,18	155,1	48	41	6	NA	0,0	25,88	25,31	-0,6	-0,06	3	7%	1	Not	Not	36,33 €	41,17 €	-12%	Not	Not Logistic Sprawl
70	Albany, United States	18720	11	Polycentric or rather polycentric	Local	Not	Not	NA	Small	Not	Not	NAICS 493	2003 - 2013	10	2003	0,84	44,9	54	64	3	NA	2013	0,88	46,8	48	55	3	NA	0,0	27,87	28,32	0,5	0,05	-6	-11%	-9	Yes	Not	NA	NA	#VALEUR!	NA	Logistic Sprawl <5km
71	Dayton, United States	4440	3	Polycentric or rather polycentric	Local	Not	Yes	Chi-Pitts	Small	Not	Not	NAICS 493	2003 - 2013	10	2003	1,04	233,8	54	52	12	NA	2013	0,99	222,4	49	50	11	NA	-0,1	21,58	28,71	7,1	0,71	-5	-9%	-2	Yes	Not	32,55 €	40,11 €	-19%	Not	Logistic Sprawl 5km - 10 km
72	Richmond, United States	11303	13	Monocentric or rather monocentric	Local	Not	Yes	Bos-Wash	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,14	100,7	58	51	5	NA	2013	1,24	110,1	87	70	8	NA	0,1	18,83	20,28	1,4	0,14	29	50%	19	Yes	Not	60,64 €	48,73 €	24%	Yes	Logistic Sprawl <5km
73	Tulsa, United States	16237	7	Polycentric or rather polycentric	Local	Not	Not	NA	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	1,00	61,5	39	39	2	NA	2013	1,08	66,6	37	34	2	NA	0,1	19,60	23,63	4,0	0,40	-2	-5%	-5	Yes	Not	46,79 €	45,43 €	3%	Yes	Logistic Sprawl <5km
74	Tucson, United States	23800	NA	Polycentric or rather polycentric	Local	Yes	Yes	Phoenix-Tucson	Medium	Not	Not	NAICS 493	2003 - 2013	10	2003	0,93	39,2	33	35	1	NA	2013	1,05	43,9	55	53	2	NA	0,1	56,66	45,80	-10,9	-1,09	22	67%	17	Not	Not	67,43 €	60,45 €	12%	Yes	Not Logistic Sprawl

Gateways NA https://transportgeography.org/?page_id=7665

US - EUR	0,9
R - EUR	0,22
Sq-m2	0,092903