An Impact of Proximity to the Subway on the short-term Rental Prices: A Case of the former USSR Cities

Abstract

This study assesses the impact of the subway proximity on the rents of short-term accommodation. Unlike majority of studies, which focus on the impact of subway in the advanced economies, this paper concentrates on the cities of the former USSR. The short-term accommodation is a rapidly developing market worldwide. We use the data of one of the branch leaders Airbnb, as having two big advantages: a wide coverage of cities and a uniform data format. The estimations are conducted using spatial models (SLM, SEM and SAC) in order to take into account the spatial dependence present. Statistically significant effects of distance to subway are obtained for Moscow. The total effect is following: the increase in distance to metro for 1 km leads to a rent decrease by around 1.47% for Moscow, 3.1% for Kiev, 2.3% for Kazan, and 3.4% for Novosibirsk.

Keywords: Spatial dependence, rents, former USSR, short-term accommodation, Airbnb.com, public transit accessibility, subway.

JEL codes: C23, O18, R38.

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1. Introduction

The relation between transport accessibility and house prices is a classical problem. One of the earliest widely cited work in this field appeared in the first half of the 19th century (Spengler 1930) and new articles are published up to now. This highlights the relevance of this research.

This study was motivated by the comparison of two subway systems: in St. Petersburg and in Samara. While metro in the former city the subway is one of the most important transport modes, in Samara it plays a minor role. This might be explained by the level of development of the subway: 67 stations and 5 lines in St. Petersburg versus 10 stations and 1 line in Samara. Another explanation lies in the configuration of the subway system. In St. Petersburg, the subway connects the core of the city with its distant parts. In Samara, like in many other cities of the former Soviet Union, the subway was initially built in order to support commuting of its citizens to the industrial sites. After the collapse of the USSR, the subway now serves vast and empty industrial areas. Thus, it does no longer satisfy the needs of the city. Only one station was built during the post-Soviet period and it is not far from one of the sights of the city — the embankment of Volga.

The subway system which differs from the others significantly is that of Moscow. It has the greatest among considering cities number of stations, the biggest number of lines, there is not only underground, but also light rail line. It is also the oldest one on post-soviet area. Nowadays Moscow has more than 200 subway stations, which cover the lion's share of the city's territory.

The topic considered here can be of interest for several economic agents. First of all, the government may be interested in the most effective budget expenditures. Making decisions about building a new station in this or that place is not obvious and many s should be taken into account, including real estate price changes in nearby neighborhoods. Another stakeholders are the real estate investors. In Alonso (1964) model, the value of the land increase with the increase of the accessibility to the central business district (CBD). However, it is not obvious whether in different areas the same increase in accessibility leads to an equal increase in land and property values. The aim of this study is to find out if the impact of proximity to subway differs significantly depending on the density and configuration of the subway network. In order to do this we take advantage of a sample of big cities from the former Soviet Union having subways, which vary in terms of the size of their subway networks. On the other hand, being created during the Soviet era, they share many common characteristics, which facilitates the comparison. For example, inclusion of cities with subway from Western Europe or North America would introduce unnecessary heterogeneity into the sample.

A critical review of literature has shown that overwhelming majority of researches focus on the cities in the advanced economies. It is important to study such cities, because of the different approaches to the city planning applied, which can lead to very different outcomes.

The research is expected to reveal the differences between impacts of the distance to the subway with respect to rents of short-term accommodation. It is expected that the effects on the rents of the short-term accommodations will be higher than on the prices and rents for the long-term accommodations. First, the owners are thought to be wealthier than the tenants and, therefore, to rely more on the private transit, thus, leading to a higher elasticity of rents than prices to the subway proximity. Second, the guests of a city depend on the public transit even more than its permanent residents, which should translate in the higher elasticity of the short-term rents with respect to the subway proximity.

The results of this study can be used by the urban planners. It is a rather common practice to calculate the percentage return from the investment in new station or line building. However, the flexible system of tax deduction on the Airbnb website and international investigation complicates such calculations, so this question is out of this study.

The paper is organized as follows. In the next section, the literature review is presented. In section 3, data are thoroughly described. Section 4 is devoted to the methodology used in this study, while section 5 discusses estimation results. In the last section, the conclusions are drawn and policy recommendations are made.

2. Literature review

According to the economic theory, real estate prices should reflect totally or partly the benefits from various facilities and transport accessibility (Agostini and Palmucci 2008; Alonso 1964, Henneberry 1998). This relationship can be modelled in the following way: an individual makes choice between buying a larger but more distant from the CBD or a smaller but closer to the CBD dwelling, given his budget constraint. As the demand for dwellings next to the central business district is higher than for the distant ones, the price reflects these differences. In a slightly different context, the individual takes into account both direct (price of tickets) and indirect (the time the individual spends to get to work) costs of travelling between his home and his workplace.

These models do not consider the negative effects, a big transport node may cause, such as noise and overcrowding. These adverse consequences can be so large that the overall effect can be negative (Armstrong 1994; Bowes and Ihlanfeldt 2001; Dornbush 1975). In general, the underground stations are not noisy. However, in some cities they are situated above the ground and, thus, produce noise. This effect may be smoothed out by adding non-linearity to the distance regressor.

One of the earliest and widely cited papers about the effects of subway on real estate values is Damm et al. (1980), where the authors use hedonic regression on transaction prices six years before the new subway is completed. They find that even news about the opening of the underground station has positive effect on prices. As a proxy for the CBD accessibility researchers calculate the Euclidean distance to the center of the city, which turns out to be statistically significant. They also include some variables describing the surroundings, which are statistically significant, too.

Gatzlaff and Smith (1993) investigate the effects of proximity to the subway in Miami. They analyze transaction prices before and after opening. What is specific about Miami is the absence of a large downtown center. After the opening the passenger traffic turned out to be smaller than expected, which can be explained by the absence of the CBD. Despite the fact that the new line raised the prices of nearby dwellings, this increase turned out to be very small. According to these results the structure of the city can play a significant role.

Another way to take the location and transport accessibility into consideration is one presented in study of Toronto metro by Bajic (1983). The author has chosen five places and counted the time a person needs to get to these places. He also added a binary choice logistic model for a choice between the use of private or public transport mode. Though this method is not considered in current work, it might be tested in future.

What is new in the paper of Agostini and Palmucci (2008) about Santiago is the question about the return of investments in addition to standard problem statement of the effect of the metro station proximity on price of the house. This means how much money may be returned into the budget by an increase in taxes followed by the increase in real estate values. According to the author's estimates, the rate of return is at least 13.3% of initial investment.

A good justification for the use of the housing rents is provided in Wang et al. (2016) study on Shanghai. The authors state that, unlike purchase prices, the rents reflect the behavior of people who need property for living, not as an investment. Moreover, in their special case, the rents are less volatile than the purchase prices. The authors use a spatial quantile hedonic regression is used and obtain the following result: the average rent tends to rise by approximately 0.4% when the apartment is 100 m closer to the nearest station.

The above mentioned works focus on the subway stations location and consider additional variables, such as distance to parks, hospitals, kindergartens, etc. However, they do not take into account the fact that two similar houses in a rich and a poor neighborhood can have different prices. This problem occurs due to the spatial dependence between the real estate prices. The most widely used models, which deal with this problem are Spatial Autoregressive Model (SLM) and Spatial Error Model (SEM). This approach is used, for instance, in the study of Trojanek and Gluszak (2017) on Warsaw. The authors analyze about 34,000 transactions from 2008 through 2015. They take into consideration only apartments, which are located within 3 km distance from the station. The researchers assume that the impact from the distance to subway decreases exponentially and beyond 3 km this impact is so small that it can be ignored. The weight matrix for spatial models is filled with inverse distances and the threshold distance is set to 100 m, according to the highest Moran's I statistic. The main focus of the work is not just to determine the effect of the distance to subway but also to compare this effect between the old and new lines. The results are following: for the old line the increase in distance for 1 km, the price decreases by around 5.8% and for the new line by 2.6%.

From the viewpoint of the present paper, two studies are especially important, since they deal with the Airbnb data. The study of Wang and Nicolau (2017) is very helpful in terms of selecting the Airbnb-specific variables. It examines the determinants of the rents for the short-term accommodation in 33 cities advertised on the Airbnb website. The authors classify their variables into five groups: 1) property features, 2) host features, 3) guests' reviews, 4) rent rules, and 5) extra amenities. The only variable, which turned out to be insignificant is requirement of the guest photo confirmation. The second study is that of Ert et al. (2016) who investigate the photos of the hosts placed on the Airbnb website. The authors notice that it is better to include into the sample only offers with at least one review. In this case, the price is the market one. Otherwise the host may have too high expectations and no one will rent his apartment.

3. Data

The rental price data are collected from the website of a large online marketplace for short-term lodging — Airbnb.[1] The choice of the Airbnb as a data source is dictated by the fact that is the only website where the real estate announcements for all the cities of interest are published. This guarantees a comparability of data thanks to the use of the identical way of collecting and representing information on accommodations. An important feature of this site is that, unlike many other real estate portals, it focuses almost entirely on the short-term accommodations that are mostly demanded by the guests than by the permanent inhabitants of the cities. Thus, the results obtained for this housing segment cannot be without any reservations generalized to the whole housing market. The data are downloaded using an API and a Python script.[2] The following algorithm is used:

1) get minimum and maximum price for filter;

2) search for all results with filters;

3) take all unique apartment IDs;

4) iterate through all IDs and collect data to a csv file;

5) delete listings with type “hostel”.

The data were collected during four days starting from the May 3, 2018. The variables included in the model together with their descriptive statistics are presented in Tables 1 and 2. The number of observations for each city is shown in Figure 21.

The list of the Airbnb regressors is similar to that of Wang and Nicolau (2017), except those that have no variability in our sample. For instance, all of the dwellings have either wired or wireless internet, or both. Our sample includes 16 cities of the former Soviet Union: eight Russian cities

[1] `https://www.airbnb.com/`.

[2] `https://github.com/iamishalkin/airbnb_vkr/blob/master/anew/air.py`

(Moscow, St. Petersburg, Yekaterinburg, Samara, Volgograd, Novosibirsk, Kazan, and Nizhniy Novgorod), three Ukrainian cities (Dnepr, Kharkov, and Kiev), one city from Belarus (Minsk), one city from Kazakhstan (Almaty), one city from Armenia (Yerevan), one city from Azerbaijan (Baku), and one from Georgia (Tbilisi). All the above mentioned cities, except Volgograd, have subway systems in the traditional sense. Volgograd has light rail, while Moscow has both traditional subway and the light rail. Tashkent (Uzbekistan) also has a subway system. Nevertheless, we decided to drop it from our sample, since Airbnb appears to be not very popular in this city, with just 26 observations available, which is clearly insufficient for econometric estimations. The choice of these cities can be justified by the common origins — the subways in most of them were founded during the existence of the Soviet Union and their design follows similar principles. For example, the distances between the stations is much larger and many stations tend to be located much deeper than their West European or North American counterparts.

A brief description of subway in each city is presented in Table 3. It contains the amount of stations, amount of lines, the year of foundation and two ratios. The first ratio is length of metro system, divided by the square of the city. The second ratio is passenger traffic divided population of the city. The cities are sorted by amount of stations in descending order.

Figure 1 shows the map of the former USSR where the cities with subway or light rail are indicated. The size of the dots is proportional to the number of stations in the corresponding subway system. Black color denotes subways, which were founded during the Soviet period, while red color denotes those opened after 1991.

For each city, geographical coordinates of the central square are determined. The central square is determined as a result of search engine query of "Central square {city}". For each lodging, the distance to center is calculated according to the *haversine* formula. It is chosen, because of its high accuracy in distance calculations. The haversine function looks like:

$$hav(\theta) = \sin^2\left(\frac{\theta}{2}\right)$$

For any two points on a sphere, i and j, the haversine of the central angle between them is given by:

$$hav\left(\frac{d_{ij}}{r}\right) = hav(\phi_j - \phi_i) + \cos(\phi_i)\cos(\phi_j)hav(\lambda_j - \lambda_i) \tag{1}$$

where d_{ij} is the is the distance between point i and point j; r is the radius of Earth; ϕ_i and ϕ_j are the latitude of point i and latitude of point j, in radians, respectively; λ_i and λ_j are the longitude of point i and longitude of point j, in radians, correspondingly.

The pairwise distances are computed as follows:

$$d_{ij} = 2r \arcsin\left(\sqrt{hav(\phi_j - \phi_i) + \cos(\phi_i)\cos(\phi_j) hav(\lambda_j - \lambda_i)}\right) \tag{2}$$

This distance is contained in the "to_centre" variable. In addition, for each city, the coordinates of all subway stations were collected from `overpass-turbo.eu` website, which, in turn, uses data from `openstreetmap.org`. Next, for each apartment the distance to the nearest subway station by roads is calculated. This is done in two steps. First, two nearest by haversine formula stations are found. Second, using Google API distance on roads is calculated to these two stations and the shortest is written to "dist_walk" column. It is important to take distance by roads, because several cities, for example St. Petersburg, lay on both sides of the river. So the situation when station is just over the river, but the bridge is quite far away is taken into account.

First, we estimate pooled regressions for all cities in our sample. The estimation results of the models with and without spatial effects are reported in Table 4. Here, all coefficients, including structural ones, must be commented upon: sign, significance, and interpretation.

As seen from Table 3, the differences between cities are dramatic. Moscow is an outlier in terms of the number of stations and lines. There are also quite developed systems like in St.Petersburg and Kiev as well as very poor system in Dnepr with only six stations. Combining all cities and performing one general model brings rather poor results. That is why we decided to perform clustering before fitting models.

For clustering the following data from `wikipedia.org` are collected: 1) the number of stations; 2) the number of lines; 3) the age of the subway; 4) the ratio of the total length of the subway lines to the area of the city; 5) the ratio of passenger traffic to the population. Then all the variables were normalized using the following formula:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{3}$$

where z_i is the new value, x_i is an old value and x is the vector of old values in certain column.

Next, Euclidean distances between points were calculated and hierarchical clustering with Wald clustering criteria Ward (1963) is performed. We decided to select four groups looking at clustering plot, see Figure: 19.

The Moscow underground system is so different from the systems in the other cities that it makes sense to consider it separately from them. With five groups Baku turns into a distinct cluster. Although Baku subway system differs from those in Kiev and St. Petersburg by the number of stations, it is still better not to consider Baku separately, because it has no outstanding features, like Moscow, for example.

4. Methodology

We start from estimating a simple hedonic OLS regression, which is typically applied in the research on residential prices. Here, we use a log-linear specification, which is advocated, for example, by Malpezzi (2003). This transformation allows interpreting the absolute changes in explanatory variables, X, as a percentage change in the dependent variable y. The second reason to perform this transformation is to make the distribution of dependent variable become more similar to normal one.

$$y = X\beta + u \tag{4}$$

where y is the vector of rents; X is the matrix of structural and locational characteristics of lodging; and u is the disturbance term.

However, the price of one dwelling is not independent from that of other dwellings, especially located nearby. Ignoring this spatial dependence can lead to biased estimation results when a simple OLS model is used. Indeed, according to the Moran's I test applied to our data, we can reject the null hypothesis of no spatial correlation in our data at any reasonable significance level. The dependence is higher the closer the dwellings are to each other. This is true because of the behavior of the owner. He decides how much his property costs looking at his neighbors. This causes spatial correlation. This study is primarily based on the papers, which use a spatial regression model approach — Bowen et al. (2001); Cohen and Coughlin (2008); Won Kim et al. (2003). The general formula for the spatial models looks like:

$$\begin{aligned} y &= X\beta + \rho W_1 y + u \\ u &= \lambda W_2 u + e \end{aligned} \tag{5}$$

where W_1 and W_2 are the spatial weight matrices measuring the proximity of observations, while ρ and λ are the coefficients measuring the degree of spatial dependence.

If ρ equals to zero, then we deal with the Spatial Error Model (SEM). If λ equals to zero than it is lag model or Spatial Autoregressive Model (SLM). If both values are not equal to zero, then we have a Spatial Autoregressive Combined Model (SAC). These models require a spatial weights matrix. There are different ways to do that, see Wilhelmsson (2002). Here, we will use the simple inverse distance method.

5. Estimation results

5.1. Pooled regressions

Here, we report estimation results for three types of models: 1) pooled models, which are estimated for all cities simultaneously; 2) city-specific models, where regressions are estimated separately for each city; and 3) cluster models, where regressions are run for groups of cities identified using the cluster analysis.

Structural characteristics. We discuss the estimated coefficients of structural characteristics of short-term accommodation only for the pooled models, given that they are similar across the three types of models considered here. The estimation results of the pooled models estimated for all cities simultaneously are reported in Table 4. The results from OLS regression without spatial correction can be compared to Wang and Nicolau (2017) paper. The difference in constant term 2.41 in Wang and Nicolau (2017) and 7.28 in this study can be explained by the difference in currency. In our paper, an inside Airbnb currency converter was used (the API requests returned prices in rubles by default). The "instant_bookable" term is positive and its value is 0.028 opposite to -0.067 in Wang and Nicolau (2017). The positive coefficient seems to have more sense as it is more comfortable for the guest to book the apartment at once, so the price should be higher. The number of bathrooms in our regression has negative sign and it is significant. This may be caused by hostels, which set the type of hosting as apartment to cheat the filters. Contrary to the Wang and Nicolau's results, this coefficient is positive, which has more sense. The number of bedrooms has relatively close coefficients in both studies, 0.100 here and 0.125 at Wang and Nicolau (2017). Free parking in Wang and Nicolau's work has positive sign, whereas in our research it is negative. Maybe this is related to the fewer automobile travellers. When free parking is mentioned it means that no security for the car is provided. In both studies, breakfast variable is negative and significant and these results are inconsistent with the researches on hotel market (Schamel 2012; Masiero et al. 2015; Yang et al. 2016). In this study the absolute value of breakfast coefficient is approximately 5 times greater and equals -0.053. If smoking is allowed, the price decreases for circa 3% in this research and 26.5% in Wang and Nicolau (2017). Reviews in our study turned out to be insignificant, though in Wang and Nicolau (2017) this coefficient is 0.009.

In Table 9, representing spatial regressions for all cities there is no column for SAC model because the distance matrix turned out to be so large that could not be allocated in memory of the used server. In the pooled models, only for Kiev the distance to subway had a statistically significant coefficient. For SEM its value is -0.0733 and for lag model the coefficient is -0.0382. The total effect is circa -6% which decomposes to 4% of direct effect and 2% of indirect effect.

5.2. City-specific regressions

Next, separate regressions for each city were estimated. Below, the estimation results concerning the distance-to-subway coefficients are discussed for each city.

Almaty. Similarly to previous regressions the separate model estimated only for Almaty revealed the insignificant coefficient of distance to subway. In both types of spatial corrections (SLM and SEM), ρ and λ are significant. However, in combined model, ρ coefficient is insignificant and and negative, so it may be assumed that spatial corrections should take place in models with rents for Almaty. It seems that spatial influence is quite complicated. It is interesting that presence of the elevator adds significantly to the rental price. Probably, this can be explained by the difference between old and new buildings.

Baku. No strong evidence that the distance to subway significantly affects rents is found for Baku. However, this coefficient is negative (-0.049) in all regressions and probably the increase of the sample size can make it significant. It is also interesting that neither ρ nor λ is significant in SLM and SEM, but when both models are combined the coefficients become significant and change their sign. With the given sample size spatial models for Baku are probably redundant.

Dnepr. Although for Dnepr there is approximately the same number of observations as for Baku, all models for Dnepr have statistically significant spatial correction coefficients. Here, the distance to subway is also insignificant, although in all models it is negative (-0.024).

Kazan. Negative significant coefficients for distance to metro are for SAC and SLM regressions without distance to centre. Their values are -0.015 and -0.014, respectively. In SLM and SAC models, it is not correct to interpret regression coefficients by themselves, instead direct, indirect, and total impacts should be calculated (LeSage and Pace 2009). The total effect for SAC model is -0.023 and for SLM regression is -0.019. The usage of spatial models is justified for Kazan as both ρ and λ are significant for all models.

Kharkov. Distance to subway has negative coefficient only for regressions without distance to center and in all models they are insignificant. In SLM and SEM regressions, ρ and λ are significant, while in the SAC model λ is not significant.

Kiev. Regressions without distance to center have negative and significant coefficient for distance to subway. In SAC, SEM, and SLM regressions, the coefficients are -0.018, -0.063, and -0.016, respectively. The total effect of additional km of distance to subway in SAC model is -0.032 and in SLM model is -0.029. The usage of SAC model may be redundant because of the insignificant λ coefficient.

Minsk. In all regressions for Minsk, the distance to subway is not statistically significant. The sign is negative for models without distance to center. In SAC model, λ is not significant, however, the spatial influence should be taken into account.

Nizhniy Novgorod. Neither ρ nor λ is significant in all the models. The distance to subway station turned out to be positive even in regressions without distance to city center.

Novosibirsk. Although the consideration of spatial effects turned out to be redundant for Novosibirsk in all regressions, the distance to subway is negative and statistically significant. The coefficient estimated in the OLS regression is -0.034.

Samara. All regressions, except SAC, have insignificant ρ and λ. In SAC model, these coefficients have opposite signs. This may probably occur because of the small sample size (only 103 observations).

St. Petersburg. The effect of the distance to the next subway station is statistically insignificant in all regressions. It has negative sign in the models without distance to the city center. The spatial effects should be taken into consideration, but the λ coefficient is insignificant for SAC model.

Tbilisi. Similar results were obtained for Tbilisi. In SAC model, the coefficient is -0.011.

Volgograd. In Volgograd, the transport mode is different from the other cities. Thus, “dist_walk” here denotes the distance to the light rail station. This distance is insignificantly different from zero in each regression.

Yekaterinburg. Here, the distance to the nearest subway station is also insignificant and its sign differs for models with and without distance to center. For SAC model, the coefficient is -0.034. Only ρ is significant in all models, except SLM with inverse distances. The use of spatial models is justified for Yekaterinburg, however, the weight matrix should be chosen carefully.

Yerevan. The number of observations for Yerevan is 773. Spatial correction coefficients are significant but the distance-to-subway coefficient is not. In SAC model, its value is -0.009.

5.3. Clusters

For each cluster, the same number of regressors is used, except the first cluster with Moscow, as it has only one city and there is no need to include “city”, “city*to_centre”, and “city*dist_walk” variables. In order to determine which model to choose (SLM or SEM), the Lagrange multiplier tests are performed. Both hypotheses of $\rho = 0$ and $\lambda = 0$ are rejected at any reasonable significance level. Therefore, Spatial Lag (SLM), Spatial Error (SEM), and Spatial Autocorrelation Combined (SAC) models are estimated, see Tables 5 through 8.

In order to check the robustness of our models, the weights are recalculated using $\frac{1}{d_{ij}^2}$ formula, where d_{ij} is a Euclidean distance between lodging i and lodging j. After estimating four models — SLM with two weight matrices and SEM with two — it turned out that distance to metro station has no significant influence on rental prices. Moreover, with “to_center” variable included the distance to subways coefficient turns to positive. Probably this occurs because distance to centre and distance to metro is quite correlated especially for the cities with weakly developed metro systems. First stations are usually situated in CBD. That is why the “to_center” regressor was deleted and both models were reestimated and SAC model was added without this distance. For SAC model, two weight matrices were used: for autoregression term inverse distances were used and for error term squared inverse distances were used. In all SLM and SAC models, ρ coefficients are positive and significant. This is consistent with the assumption that owner of the apartment looks at apartments nearby when setting market rental price. In all SEM, λ is also significant and positive, however, in SAC models it is significant only for the fourth cluster.

The majority of coefficients are similar across all the models and the change in sign is present only for insignificant variables. It shows the robustness of the models.

First cluster. The first cluster includes only Moscow city. It is the only cluster where distance to subway station turned out to be significant. The direct effect of decreasing the distance to metro station by 1 km leads to a round 1% increase of rent. The indirect effect is -0.4%, so the total effect is -1.4%. The breakfast coefficient has an unexpected negative sign and is significant. Probably, the owners of cheap apartments with not the best conditions try to attract visitors by offering breakfast.

Second cluster. The second cluster includes Baku, Kiev, and St. Petersburg. Baku is set as a base city for cross-effect variables. Although the distance to subway station coefficient is negative here, it is insignificant. The total effect for Almaty is about -4.5%, while for Kiev and for St. Petersburg it insignificantly differs from Almaty case. Interpreting the “city” variable coefficient it might be concluded that an average rent is higher in St. Petersburg for 95% confidence level and even even more higher in Kiev for 99% confidence level.

Third cluster. The third cluster includes Minsk and Kharkov. Kharkov is set as a base city for cross-effect variables. Here, the distance to the city center also turned out to be insignificant and is more positive for Kharkov. Probably there are too few observations for Kharkov (336). The problem with Airbnb data is the absence of the size of the apartment. The closer the apartment to the subway station, the more expensive it is. On the contrary, the smaller the apartment the lower is the rent asked for it. It might be the case, that people invest in small apartments and earn money from renting them out on Airbnb. Some disproportion might occur and the coefficient can become positive and insignificant. When interpreting the coefficient of the “city” variable it can be concluded that apartments in Kharkov are generally cheaper than in Minsk.

Fourth cluster. The fourth cluster includes cities with the least developed subway systems, namely: Almaty, Kazan, Volgograd, Novosibirsk, Dnepr, Yekaterinburg, Samara, Tbilisi, Yerevan, and Nizhniy Novgorod. Almaty is set as a base city for cross-effect variables. Although the coefficient of “dist_walk” is negative, it is insignificant. The Dnepr, Nizhniy Novgorod, Samara, and Volgograd subway systems have positive coefficients. It is is the only regression, where λ coefficient is significant, however it is negative. The problem with the fourth cluster might be the same as for the third — a small number of observations for cities in the cluster.

6. Conclusion

In this paper, we considered the effects of proximity to subway on the rents for short-term accommodation. This relationship was investigated using 16 cities with subway or light rail of the former Soviet Union.

Three types of regressions were tested — pooled (all cities), clustered (groups of cities), and individual (for each city separately). It turned out that, despite the problems with the limited number of observations in regressions for each city, this type of modelling gives more information than clustered and pooled regressions. Moreover, results for distinct cities do not contradict the results for pooled and clustered models.

A statistically significant effect of distance to subway on the rents for short-term accommodation was detected in the cases of Moscow, Kiev, Novosibirsk, and Kazan. The total effect is following: the increase in distance to metro for 1 km leads to a rent decrease by around 1.47% for Moscow, 3.1% for Kiev, 2.3% for Kazan, and 3.4% for Novosibirsk. The effect turns out to be smaller than in Wang et al. (2016) paper. Probably this is because in considered cities the subway system is less developed than Shanghai, even in Moscow.

This study also shows that similar subway systems can exert different effects on rents. This is probably related to the peculiarities of the Soviet subway construction. Nice example in this respect is the subway in two cities located on the river Volga: Samara and Kazan. The first was built during the Soviet period and the latter was constructed by 2005. According to our results, the subway in Kazan is more important for visitors and citizens than in Samara and this is reflected in the rents for the Airbnb accommodation.

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Appendix

Table 1: Descriptive statistics: numerical variables

Statistic	Mean	St. dev.	Minimum	Maximum
price, rubles/night	2,360	2,072	570	125,664
dist_walk, meters	1,364.8	1,697.8	0	14,958.0
to_centre, meters	4,298.3	4,372.0	8.8	29,197.4
Internet	1	0	1	1
bathrooms	1.1	0.5	0	8
bedrooms	1.3	0.8	0	8
beds	2.1	1.5	1	10
min_nights	1.8	1.4	1	25
person_capacity	3.8	1.8	1	16
picture_count	17.9	11.4	1	177
review_rating_value	9.5	1.1	2	10
latitude	52.152	6.658	40.098	60.118
longitude	39.484	11.288	27.339	83.018

Table 2: Descriptive statistics: binary variables

Variable	**n**	%	∑%
Air_conditioning	8737	50.6	100.0
Breakfast	1679	9.7	100.0
Hair_dryer	14367	83.2	100.0
Elevator_in_building	9549	55.3	100.0
Essentials	16617	96.2	100.0
Family_kid_friendly	12920	74.8	100.0
Free_parking_on_premises	10045	58.1	100.0
Free_parking_on_street	5809	33.6	100.0

Variable	**n**	%	∑ %
Iron	15160	87.8	100.0
Kitchen	16692	96.6	100.0
Pets_allowed	2683	15.5	100.0
Self_Check_In	2638	15.3	100.0
Smoke_detector	5443	31.5	100.0
Smoking_allowed	2517	14.6	100.0
Suitable_for_events	1350	7.8	100.0
TV	15319	88.7	100.0
Washer	15976	92.5	100.0
Wireless_Internet	16877	97.7	100.0
instant_bookable	11571	67.0	100.0

Table 3: Description of the subway systems in our sample

	City	Number of stations	Number of lines	Foundation year	Length-to-area ratio	Traffic-to-population ratio
1	Moscow	245	12	1935	0.142	0.510
2	St. Petersbug	70	5	1955	0.081	0.202
3	Kiev	53	3	1960	0.080	0.155
4	Kharkov	30	3	1975	0.114	0.006
5	Minsk	29	2	1984	0.107	0.058
6	Baku	24	3	1967	0.017	0.204
7	Tbilisi	23	2	1966	0.037	0.065
8	Volgograd	21	2	1984	0.020	0.016
9	Nizhniy Novgorod	14	2	1985	0.046	0.013
10	Novosibirsk	13	2	1985	0.031	0.027
11	Yerevan	10	1	1981	0.054	0.003
12	Samara	10	1	1987	0.027	0.007
13	Kazan	10	1	2005	0.037	0.015
14	Almaty	9	1	2011	0.017	0.003
15	Yekaterinburg	9	1	1991	0.027	0.017
16	Dnepr	6	1	1995	0.018	0.003

Table 4: OLS on all cities

Explanatory variables	*Dependent variable:*
	log(price)
Baku	-0.281^{***}
	(0.061)
Dnepr	-0.226^{**}
	(0.092)
Yekaterinburg	-0.075
	(0.048)
Yerevan	-0.007
	(0.040)
Kazan	-0.145^{***}
	(0.043)
Kharkov	-0.178^{***}
	(0.052)
Kiev	0.106^{***}
	(0.037)
Minsk	-0.069
	(0.044)
Moscow	0.199^{***}
	(0.037)
N_Novgorod	-0.102^{**}
	(0.047)
Novosibirsk	-0.143^{***}
	(0.049)
Saint_Petersburg	-0.169^{***}
	(0.037)
Samara	-0.369^{***}

Table4 – continued from previous page

Explanatory variables	Coefficients
	(0.081)
Tbilisi	-0.084^{**}
	(0.037)
volgograd	-0.219^{***}
	(0.063)
dist_walk	0.00002
	(0.00002)
to_centre	-0.00003^{*}
	(0.00002)
Air_conditioning	0.125^{***}
	(0.008)
Breakfast	-0.053^{***}
	(0.010)
Hair_dryer	0.0004
	(0.011)
Elevator_in_building	0.061^{***}
	(0.007)
Family_kid_friendly	0.013^{*}
	(0.007)
Free_parking_on_premises	-0.016^{**}
	(0.006)
Free_parking_on_street	-0.028^{***}
	(0.007)
Iron	-0.008
	(0.012)
Pets_allowed	-0.004
	(0.009)
Self_Check_In	0.010

Table4 – continued from previous page

Explanatory variables	Coefficients
	(0.009)
Smoke_detector	0.027^{***}
	(0.007)
Smoking_allowed	-0.029^{***}
	(0.009)
Suitable_for_events	0.002
	(0.012)
TV	0.151^{***}
	(0.010)
Washer	-0.030^{**}
	(0.012)
bathrooms	-0.046^{***}
	(0.007)
bedrooms	0.100^{***}
	(0.005)
beds	-0.064^{***}
	(0.004)
(cancellation_policy)moderate	0.032^{***}
	(0.007)
(cancellation_policy)strict	0.028^{**}
	(0.011)
cancellation_policy: strict_14_with_grace_period	0.036^{***}
	(0.009)
min_nights	-0.013^{***}
	(0.002)
person_capacity	0.082^{***}
	(0.003)

Table4 – continued from previous page

Explanatory variables	Coefficients
picture_count	0.003^{***}
	(0.0003)
instant_bookable	0.028^{***}
	(0.007)
review_rating_value	-0.002
	(0.003)
Baku:dist_walk	-0.0001^{*}
	(0.00004)
Dnepr:dist_walk	0.00003
	(0.00003)
Yekaterinburg:dist_walk	-0.00000
	(0.00002)
Yerevan:dist_walk	-0.00001
	(0.00003)
Kazan:dist_walk	-0.00002
	(0.00002)
Kharkov:dist_walk	-0.00000
	(0.00004)
Kiev:dist_walk	-0.00000
	(0.00002)
Minsk:dist_walk	-0.00002
	(0.00002)
Moscow:dist_walk	-0.00001
	(0.00002)
N_Novgorod:dist_walk	-0.00001
	(0.00002)
Novosibirsk:dist_walk	-0.00003
	(0.00003)

Table4 – continued from previous page

Explanatory variables	Coefficients
Saint_Petersburg:dist_walk	-0.00001
	(0.00002)
Samara:dist_walk	-0.00004
	(0.00003)
Tbilisi:dist_walk	0.00001
	(0.00002)
volgograd:dist_walk	0.00002
	(0.00003)
Baku:to_centre	0.00002
	(0.00002)
Dnepr:to_centre	-0.0001^{***}
	(0.00004)
Yekaterinburg:to_centre	-0.00001
	(0.00002)
Yerevan:to_centre	-0.00000
	(0.00002)
Kazan:to_centre	0.00002
	(0.00002)
Kharkov:to_centre	-0.00003^{*}
	(0.00002)
Kiev:to_centre	-0.00002
	(0.00002)
Minsk:to_centre	0.00000
	(0.00002)
Moscow:to_centre	0.00001
	(0.00002)
N_Novgorod:to_centre	0.00002
	(0.00002)

Table4 – continued from previous page

Explanatory variables	Coefficients
Novosibirsk:to_centre	0.00001
	(0.00002)
Saint_Petersburg:to_centre	0.00002
	(0.00002)
Samara:to_centre	0.00003
	(0.00002)
Tbilisi:to_centre	−0.00001
	(0.00002)
Volgograd:to_centre	−0.00002
	(0.00002)
Constant	7.248***
	(0.047)
Observations	17,275
R^2	0.324
Adjusted R^2	0.321
Residual Std. Error	0.390 (df = 17201)
F Statistic	112.900*** (df = 73; 17201)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression results for the first cluster (Moscow)

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
(Intercept)	5.4221^{***}	6.0544^{***}	5.0811^{***}	7.5298^{***}	7.5149^{***}	7.4425^{***}	5.0010^{***}
	(0.2327)	(0.1793)	(0.2191)	(0.0787)	(0.0786)	(0.0779)	(0.3324)
dist_walk	0.0024	0.0037	-0.0103^{**}	0.0057	0.0063	-0.0178^{***}	-0.0101^{**}
	(0.0046)	(0.0046)	(0.0038)	(0.0062)	(0.0056)	(0.0053)	(0.0038)
to_centre	-0.0083^{***}	-0.0099^{***}		-0.0142^{***}	-0.0141^{***}		
	(0.0018)	(0.0017)		(0.0022)	(0.0020)		
Air_conditioning	0.0666^{***}	0.0667^{***}	0.0770^{***}	0.0664^{***}	0.0667^{***}	0.0774^{***}	0.0769^{***}
	(0.0152)	(0.0152)	(0.0151)	(0.0154)	(0.0154)	(0.0153)	(0.0151)
Breakfast	-0.0601^{**}	-0.0594^{**}	-0.0549^{*}	-0.0605^{**}	-0.0597^{**}	-0.0549^{*}	-0.0549^{*}
	(0.0218)	(0.0218)	(0.0218)	(0.0221)	(0.0221)	(0.0222)	(0.0218)
Hair_dryer	−0.0324	−0.0293	−0.0252	−0.0367	−0.0339	−0.0286	−0.0250
	(0.0243)	(0.0243)	(0.0242)	(0.0244)	(0.0245)	(0.0245)	(0.0242)
Elevator_in_building	0.0253	0.0287	0.0180	0.0256	0.0299	0.0178	0.0179
	(0.0162)	(0.0162)	(0.0161)	(0.0167)	(0.0167)	(0.0168)	(0.0161)
Family_kid_friendly	0.0489^{**}	0.0489^{**}	0.0472^{**}	0.0530^{**}	0.0528^{**}	0.0511^{**}	0.0469^{**}
	(0.0162)	(0.0162)	(0.0162)	(0.0163)	(0.0163)	(0.0163)	(0.0162)

Table5 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
Free_parking_on_premises	0.0082	0.0046	-0.0020	0.0102	0.0077	-0.0013	-0.0019
	(0.0146)	(0.0146)	(0.0144)	(0.0149)	(0.0149)	(0.0149)	(0.0144)
Free_parking_on_street	-0.0328^{*}	-0.0357^{*}	-0.0490^{**}	-0.0281	-0.0317	-0.0452^{**}	-0.0489^{**}
	(0.0166)	(0.0166)	(0.0162)	(0.0170)	(0.0170)	(0.0169)	(0.0162)
Iron	0.0088	0.0066	0.0069	0.0122	0.0098	0.0107	0.0069
	(0.0282)	(0.0283)	(0.0283)	(0.0284)	(0.0284)	(0.0285)	(0.0283)
Pets_allowed	0.0421^{*}	0.0418^{*}	0.0411^{*}	0.0404^{*}	0.0406^{*}	0.0392^{*}	0.0412^{*}
	(0.0189)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0190)
Self_Check_In	-0.0136	-0.0125	-0.0097	-0.0162	-0.0142	-0.0127	-0.0096
	(0.0197)	(0.0197)	(0.0198)	(0.0199)	(0.0199)	(0.0200)	(0.0197)
Smoke_detector	0.0299	0.0306	0.0275	0.0287	0.0261	0.0271	0.0277
	(0.0161)	(0.0161)	(0.0161)	(0.0164)	(0.0164)	(0.0164)	(0.0161)
Smoking_allowed	-0.0404	-0.0418	-0.0382	-0.0367	-0.0389	-0.0348	-0.0384
	(0.0227)	(0.0227)	(0.0227)	(0.0230)	(0.0231)	(0.0232)	(0.0227)
Suitable_for_events	0.0263	0.0254	0.0260	0.0241	0.0233	0.0228	0.0260
	(0.0357)	(0.0357)	(0.0358)	(0.0358)	(0.0360)	(0.0360)	(0.0358)
TV	0.1667^{***}	0.1678^{***}	0.1582^{***}	0.1708^{***}	0.1730^{***}	0.1620^{***}	0.1577^{***}

Table5 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0214)	(0.0214)	(0.0213)	(0.0215)	(0.0216)	(0.0216)	(0.0213)
Washer	−0.0656	−0.0640	−0.0653	−0.0568	−0.0537	−0.0554	−0.0661
	(0.0357)	(0.0357)	(0.0357)	(0.0363)	(0.0364)	(0.0366)	(0.0357)
bathrooms	−0.0261	−0.0212	−0.0189	−0.0298	−0.0232	−0.0222	−0.0193
	(0.0213)	(0.0213)	(0.0212)	(0.0218)	(0.0221)	(0.0219)	(0.0212)
bedrooms	0.0752***	0.0743***	0.0768***	0.0728***	0.0727***	0.0747***	0.0769***
	(0.0132)	(0.0132)	(0.0133)	(0.0134)	(0.0133)	(0.0134)	(0.0132)
beds	−0.1071***	−0.1079***	−0.1084***	−0.1065***	−0.1073***	−0.1078***	−0.1083***
	(0.0101)	(0.0101)	(0.0101)	(0.0102)	(0.0101)	(0.0102)	(0.0101)
(cancellation_policy)	0.0288	0.0291	0.0354	0.0280	0.0293	0.0350	0.0352
moderate	(0.0183)	(0.0183)	(0.0183)	(0.0185)	(0.0185)	(0.0186)	(0.0183)
(cancellation_policy)	−0.0532	−0.0538	−0.0490	−0.0470	−0.0517	−0.0426	−0.0493
strict	(0.0322)	(0.0323)	(0.0323)	(0.0328)	(0.0328)	(0.0330)	(0.0322)
(cancellation_policy)	0.0494**	0.0493**	0.0648***	0.0517**	0.0521**	0.0677***	0.0644***
strict_14_with_grace_period	(0.0188)	(0.0188)	(0.0186)	(0.0190)	(0.0190)	(0.0189)	(0.0186)
min_nights	−0.0093*	−0.0098*	−0.0087*	−0.0097*	−0.0103*	−0.0093*	−0.0086*
	(0.0042)	(0.0042)	(0.0042)	(0.0043)	(0.0043)	(0.0043)	(0.0042)

Table5 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
person_capacity	0.0991***	0.0995***	0.1008***	0.0999***	0.0999***	0.1018***	0.1007***
	(0.0082)	(0.0082)	(0.0082)	(0.0083)	(0.0083)	(0.0083)	(0.0082)
picture_count	0.0016*	0.0016*	0.0017*	0.0016*	0.0017*	0.0017*	0.0017*
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
instant_bookable	0.0873***	0.0878***	0.0933***	0.0867***	0.0881***	0.0932***	0.0931***
	(0.0154)	(0.0154)	(0.0153)	(0.0156)	(0.0156)	(0.0156)	(0.0153)
review_rating_value	−0.0054	−0.0054	−0.0056	−0.0054	−0.0053	−0.0057	−0.0056
	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
ρ	0.2655***	0.1852***	0.3018***				0.3122***
	(0.0277)	(0.0204)	(0.0263)				(0.0415)
λ				0.2741***	0.1885***	0.3070***	−0.0121
				(0.0294)	(0.0217)	(0.0286)	(0.0370)
Num. obs.	3419	3419	3419	3419	3419	3419	3419
Parameters	31	31	30	31	31	30	31
Log Likelihood	-1797.5035	-1799.4679	-1808.5327	-1802.7600	-1804.3476	-1822.5137	-1808.4778
AIC (Linear model)	3741.9492	3741.9492	3798.2056	3741.9492	3741.9492	3798.2056	3798.2056
AIC (Spatial model)	3657.0070	3660.9358	3677.0654	3667.5199	3670.6952	3705.0274	3678.9555

Table5 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
LR test: statistic	86.9422	83.0134	123.1402	76.4293	73.2540	95.1782	123.2500
LR test: p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Regression results for the first cluster, that includes Moscow. From left to right: 1) Spatial Lag Model with inverted distance weights matrix 2) Spatial Lag Model with squared inverted distance weights matrix 3) Spatial Lag Model without distance to centre regressor 4) Spatial Error Model with inverted distance weights matrix 5) Spatial Error Model with squared inverted distance weights matrix 6) Spatial Error Model without distance to centre regressor 7) Spatial Autoregressive Combined Model without distance to centre regressor

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: Regression results for the second cluster (Baku, Kiev, St. Petersburg)

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
(Intercept)	4.4513^{***}	5.3476^{***}	3.7649^{***}	6.9180^{***}	6.9315^{***}	6.8714^{***}	3.9199^{***}
	(0.2132)	(0.1499)	(0.1888)	(0.1066)	(0.0950)	(0.1011)	(0.2538)
Kiev	0.2167^{***}	0.2799^{***}	0.1594^{**}	0.4137^{***}	0.4054^{***}	0.3883^{***}	0.1697^{**}
	(0.0648)	(0.0637)	(0.0539)	(0.0928)	(0.0789)	(0.0866)	(0.0561)
St. Petersburg	0.1071	0.1065	0.1075^{*}	0.1228	0.1171	0.1313	0.1083^{*}
	(0.0641)	(0.0640)	(0.0540)	(0.0935)	(0.0797)	(0.0871)	(0.0552)
dist_walk	-0.0294	-0.0368	-0.0280	-0.0235	-0.0382	-0.0132	-0.0283
	(0.0438)	(0.0437)	(0.0417)	(0.0592)	(0.0529)	(0.0633)	(0.0427)
to_centre	-0.0102	-0.0103		-0.0147	-0.0113		
	(0.0204)	(0.0203)		(0.0305)	(0.0258)		
Air_conditioning	0.1346^{***}	0.1355^{***}	0.1451^{***}	0.1334^{***}	0.1343^{***}	0.1405^{***}	0.1453^{***}
	(0.0146)	(0.0146)	(0.0145)	(0.0148)	(0.0147)	(0.0148)	(0.0146)
Breakfast	-0.0521^{**}	-0.0511^{**}	-0.0490^{**}	-0.0524^{**}	-0.0523^{**}	-0.0507^{**}	-0.0491^{**}
	(0.0170)	(0.0170)	(0.0171)	(0.0170)	(0.0170)	(0.0171)	(0.0171)
Hair_dryer	0.0231	0.0263	0.0308	0.0216	0.0276	0.0265	0.0314
	(0.0183)	(0.0183)	(0.0184)	(0.0183)	(0.0183)	(0.0183)	(0.0184)

Table6 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
Elevator_in_building	0.0556^{***}	0.0549^{***}	0.0335^{***}	0.0599^{***}	0.0570^{***}	0.0444^{***}	0.0336^{***}
	(0.0102)	(0.0102)	(0.0095)	(0.0108)	(0.0107)	(0.0106)	(0.0096)
Family_kid_friendly	0.0037	0.0029	0.0042	0.0043	0.0028	0.0048	0.0041
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0104)	(0.0103)
Free_parking_on_premises	-0.0196^{*}	-0.0192^{*}	-0.0291^{**}	−0.0179	−0.0176	-0.0242^{*}	-0.0289^{**}
	(0.0093)	(0.0093)	(0.0093)	(0.0095)	(0.0095)	(0.0095)	(0.0093)
Free_parking_on_street	−0.0148	−0.0161	−0.0162	−0.0130	−0.0151	−0.0133	−0.0162
	(0.0096)	(0.0096)	(0.0096)	(0.0097)	(0.0096)	(0.0097)	(0.0096)
Iron	0.0130	0.0109	0.0099	0.0102	0.0063	0.0080	0.0092
	(0.0204)	(0.0204)	(0.0204)	(0.0204)	(0.0204)	(0.0204)	(0.0205)
Pets_allowed	−0.0177	−0.0168	−0.0193	−0.0203	−0.0192	−0.0222	−0.0195
	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0135)	(0.0135)
Self_Check_In	0.0114	0.0098	0.0149	0.0077	0.0051	0.0080	0.0140
	(0.0128)	(0.0128)	(0.0128)	(0.0129)	(0.0129)	(0.0130)	(0.0128)
Smoke_detector	0.0364^{***}	0.0351^{***}	0.0301^{**}	0.0351^{***}	0.0341^{**}	0.0302^{**}	0.0298^{**}
	(0.0102)	(0.0102)	(0.0102)	(0.0105)	(0.0105)	(0.0105)	(0.0103)
Smoking_allowed	−0.0278	−0.0298	−0.0287	−0.0243	−0.0259	−0.0231	−0.0282

Table6 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0154)	(0.0153)	(0.0154)	(0.0154)	(0.0154)	(0.0154)	(0.0154)
Suitable_for_events	−0.0077	−0.0069	−0.0081	−0.0058	−0.0072	−0.0057	−0.0081
	(0.0215)	(0.0214)	(0.0215)	(0.0216)	(0.0215)	(0.0216)	(0.0216)
TV	0.1625***	0.1625***	0.1578***	0.1635***	0.1637***	0.1596***	0.1581***
	(0.0150)	(0.0149)	(0.0150)	(0.0151)	(0.0151)	(0.0152)	(0.0150)
Washer	−0.0684***	−0.0672***	−0.0666***	−0.0684***	−0.0648***	−0.0656***	−0.0662***
	(0.0189)	(0.0188)	(0.0189)	(0.0190)	(0.0191)	(0.0191)	(0.0190)
bathrooms	−0.0603***	−0.0595***	−0.0588***	−0.0614***	−0.0612***	−0.0611***	−0.0590***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0136)	(0.0135)	(0.0136)
bedrooms	0.0738***	0.0737***	0.0726***	0.0753***	0.0749***	0.0746***	0.0729***
	(0.0088)	(0.0088)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)
beds	−0.0488***	−0.0495***	−0.0510***	−0.0471***	−0.0478***	−0.0482***	−0.0509***
	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0065)
(cancellation_policy)	0.0297**	0.0289*	0.0341**	0.0309**	0.0297*	0.0346**	0.0342**
moderate	(0.0115)	(0.0114)	(0.0114)	(0.0115)	(0.0115)	(0.0116)	(0.0115)
(cancellation_policy)	0.0346*	0.0373**	0.0434**	0.0324*	0.0364*	0.0374**	0.0437**
strict	(0.0140)	(0.0140)	(0.0140)	(0.0142)	(0.0142)	(0.0143)	(0.0140)

Table6 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
(cancellation_policy)	0.0091	0.0098	0.0123	0.0103	0.0106	0.0126	0.0126
strict_14_with_grace_period	(0.0142)	(0.0142)	(0.0142)	(0.0143)	(0.0143)	(0.0144)	(0.0143)
min_nights	-0.0165^{***}	-0.0165^{***}	-0.0169^{***}	-0.0164^{***}	-0.0163^{***}	-0.0165^{***}	-0.0169^{***}
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
person_capacity	0.0831^{***}	0.0836^{***}	0.0858^{***}	0.0827^{***}	0.0833^{***}	0.0847^{***}	0.0860^{***}
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
picture_count	0.0030^{***}	0.0031^{***}	0.0032^{***}	0.0030^{***}	0.0031^{***}	0.0031^{***}	0.0032^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
instant_bookable	−0.0018	0.0003	0.0005	−0.0005	0.0009	0.0017	0.0009
	(0.0098)	(0.0098)	(0.0098)	(0.0099)	(0.0099)	(0.0099)	(0.0098)
review_rating_value	0.0048	0.0037	0.0045	0.0044	0.0029	0.0040	0.0042
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Kiev:dist_walk	0.0288	0.0368	0.0017	0.0139	0.0342	−0.0564	−0.0001
	(0.0444)	(0.0444)	(0.0423)	(0.0602)	(0.0538)	(0.0643)	(0.0433)
St. Petersburg:dist_walk	0.0364	0.0440	0.0258	0.0328	0.0468	0.0095	0.0260
	(0.0440)	(0.0439)	(0.0419)	(0.0596)	(0.0533)	(0.0638)	(0.0429)
Kiev:to_centre	−0.0152	−0.0229		−0.0309	−0.0352		

Table6 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0207)	(0.0206)		(0.0308)	(0.0261)		
St. Petersburg:to_centre	0.0023	0.0019		0.0041	0.0010		
	(0.0204)	(0.0204)		(0.0306)	(0.0259)		
ρ	0.3333^{***}	0.2137^{***}	0.4226^{***}				0.4017^{***}
	(0.0266)	(0.0170)	(0.0235)				(0.0329)
λ				0.3493^{***}	0.2167^{***}	0.4606^{***}	0.0271
				(0.0287)	(0.0182)	(0.0254)	(0.0266)
Num. obs.	6308	6308	6308	6308	6308	6308	6308
Parameters	37	37	34	37	37	34	35
Log Likelihood	-2326.6495	-2322.5023	-2359.2030	-2337.2762	-2334.1330	-2384.6121	-2358.6993
AIC (Linear model)	4871.4707	4871.4707	5091.3355	4871.4707	4871.4707	5091.3355	5091.3355
AIC (Spatial model)	4727.2990	4719.0046	4786.4059	4748.5524	4742.2661	4837.2241	4787.3985
LR test: statistic	146.1717	154.4661	306.9296	124.9183	131.2046	256.1114	307.9370
LR test: p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Regression results for the second cluster, that includes Baku, Kiev and St. Petersburg. From left to right: 1) Spatial Lag Model with inverted distance weights matrix 2) Spatial Lag Model with squared inverted distance weights matrix 3) Spatial Lag Model without distance to centre regressor 4) Spatial Error Model with inverted distance weights matrix 5) Spatial Error Model with squared inverted distance weights matrix 6) Spatial Error Model without distance to centre regressor 7) Spatial Autoregressive Combined Model without distance to centre regressor

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 7: Regression results for the third cluster (Minsk, Kharkov)

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
(Intercept)	4.9051^{***}	5.5070^{***}	4.4521^{***}	6.9584^{***}	6.9718^{***}	6.9121^{***}	4.0448^{***}
	(0.3927)	(0.3011)	(0.3638)	(0.1127)	(0.1116)	(0.1124)	(0.4792)
Minsk	0.1564^{***}	0.1632^{***}	0.1548^{***}	0.1611^{**}	0.1676^{**}	0.1732^{**}	0.1502^{***}
	(0.0472)	(0.0473)	(0.0434)	(0.0598)	(0.0558)	(0.0567)	(0.0416)
dist_walk	0.0322	0.0406	−0.0003	0.0295	0.0411	−0.0207	0.0017
	(0.0387)	(0.0387)	(0.0361)	(0.0457)	(0.0445)	(0.0456)	(0.0342)
to_centre	-0.0275^{*}	-0.0336^{**}		-0.0454^{**}	-0.0469^{***}		
	(0.0119)	(0.0117)		(0.0150)	(0.0138)		
Air_conditioning	0.1645^{***}	0.1675^{***}	0.1691^{***}	0.1688^{***}	0.1712^{***}	0.1726^{***}	0.1658^{***}
	(0.0281)	(0.0282)	(0.0281)	(0.0286)	(0.0286)	(0.0288)	(0.0279)
Breakfast	−0.0754	−0.0726	−0.0774	−0.0737	−0.0726	−0.0740	−0.0771
	(0.0412)	(0.0412)	(0.0413)	(0.0411)	(0.0412)	(0.0410)	(0.0410)
Hair_dryer	−0.0598	−0.0631	−0.0536	−0.0780	−0.0805	−0.0795	−0.0437
	(0.0518)	(0.0519)	(0.0519)	(0.0519)	(0.0520)	(0.0519)	(0.0515)
Elevator_in_building	−0.0082	−0.0090	−0.0202	−0.0107	−0.0090	−0.0225	−0.0191
	(0.0228)	(0.0228)	(0.0224)	(0.0246)	(0.0244)	(0.0248)	(0.0218)

Table7 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
Family_kid_friendly	−0.0113	−0.0100	−0.0152	−0.0164	−0.0147	−0.0210	−0.0136
	(0.0269)	(0.0270)	(0.0270)	(0.0271)	(0.0270)	(0.0272)	(0.0268)
Free_parking_on_premises	−0.0155	−0.0134	−0.0156	−0.0161	−0.0153	−0.0168	−0.0156
	(0.0267)	(0.0268)	(0.0268)	(0.0268)	(0.0269)	(0.0268)	(0.0266)
Free_parking_on_street	−0.0657**	−0.0676**	−0.0678**	−0.0597*	−0.0625*	−0.0585*	−0.0693**
	(0.0249)	(0.0249)	(0.0249)	(0.0250)	(0.0250)	(0.0250)	(0.0247)
Iron	0.0140	0.0137	0.0078	0.0251	0.0225	0.0240	0.0029
	(0.0532)	(0.0532)	(0.0532)	(0.0527)	(0.0529)	(0.0527)	(0.0531)
Pets_allowed	−0.0206	−0.0185	−0.0239	−0.0238	−0.0207	−0.0291	−0.0228
	(0.0295)	(0.0295)	(0.0296)	(0.0298)	(0.0298)	(0.0299)	(0.0293)
Self_Check_In	−0.0333	−0.0300	−0.0288	−0.0331	−0.0290	−0.0284	−0.0306
	(0.0349)	(0.0349)	(0.0349)	(0.0351)	(0.0350)	(0.0352)	(0.0347)
Smoke_detector	0.0192	0.0206	0.0210	0.0232	0.0257	0.0264	0.0173
	(0.0246)	(0.0246)	(0.0246)	(0.0247)	(0.0247)	(0.0247)	(0.0245)
Smoking_allowed	0.0439	0.0436	0.0370	0.0460	0.0469	0.0410	0.0349
	(0.0339)	(0.0339)	(0.0339)	(0.0339)	(0.0340)	(0.0339)	(0.0337)
Suitable_for_events	−0.0879	−0.0930*	−0.0765	−0.0999*	−0.1103*	−0.0935*	−0.0679

Table7 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0467)	(0.0468)	(0.0467)	(0.0472)	(0.0472)	(0.0474)	(0.0463)
TV	0.1441**	0.1379*	0.1383*	0.1473**	0.1363*	0.1415*	0.1414**
	(0.0537)	(0.0538)	(0.0538)	(0.0547)	(0.0549)	(0.0550)	(0.0530)
Washer	0.0495	0.0518	0.0479	0.0529	0.0580	0.0525	0.0441
	(0.0342)	(0.0343)	(0.0343)	(0.0345)	(0.0344)	(0.0346)	(0.0340)
bathrooms	−0.0625**	−0.0663**	−0.0637**	−0.0637**	−0.0687***	−0.0636**	−0.0608**
	(0.0202)	(0.0202)	(0.0202)	(0.0211)	(0.0209)	(0.0214)	(0.0199)
bedrooms	0.0793***	0.0805***	0.0772***	0.0789***	0.0802***	0.0764***	0.0768***
	(0.0160)	(0.0160)	(0.0160)	(0.0166)	(0.0165)	(0.0168)	(0.0158)
beds	−0.0768***	−0.0760***	−0.0757***	−0.0766***	−0.0743***	−0.0759***	−0.0763***
	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0164)	(0.0163)
(cancellation_policy)	0.0117	0.0116	0.0158	0.0124	0.0083	0.0145	0.0174
moderate	(0.0294)	(0.0294)	(0.0294)	(0.0294)	(0.0294)	(0.0294)	(0.0293)
(cancellation_policy)	0.0567	0.0577*	0.0681*	0.0522	0.0535	0.0594*	0.0698*
strict	(0.0291)	(0.0291)	(0.0288)	(0.0290)	(0.0291)	(0.0289)	(0.0287)
(cancellation_policy)	0.0661	0.0666	0.0656	0.0643	0.0660	0.0613	0.0665
strict_14_with_grace_period	(0.0405)	(0.0406)	(0.0406)	(0.0406)	(0.0408)	(0.0408)	(0.0404)

Table7 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
min_nights	−0.0063	−0.0063	−0.0067	−0.0071	−0.0079	−0.0076	−0.0060
	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0075)	(0.0074)
person_capacity	0.0927***	0.0928***	0.0938***	0.0933***	0.0923***	0.0947***	0.0934***
	(0.0111)	(0.0111)	(0.0111)	(0.0112)	(0.0111)	(0.0112)	(0.0111)
picture_count	0.0047***	0.0047***	0.0049***	0.0049***	0.0049***	0.0051***	0.0047***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
instant_bookable	0.0274	0.0299	0.0291	0.0247	0.0273	0.0259	0.0291
	(0.0226)	(0.0227)	(0.0227)	(0.0228)	(0.0229)	(0.0229)	(0.0225)
review_rating_value	0.0059	0.0049	0.0052	0.0038	0.0029	0.0025	0.0067
	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0087)
Minsk:dist_walk	−0.0302	−0.0387	−0.0096	−0.0306	−0.0412	−0.0002	−0.0101
	(0.0399)	(0.0399)	(0.0367)	(0.0475)	(0.0461)	(0.0470)	(0.0348)
Minsk:to_centre	0.0126	0.0161		0.0236	0.0244		
	(0.0128)	(0.0127)		(0.0169)	(0.0154)		
ρ	0.2669***	0.1889***	0.3238***				0.3760***
	(0.0504)	(0.0378)	(0.0470)				(0.0635)
λ				0.2727***	0.1956***	0.3463***	−0.0735

Table7 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
				(0.0559)	(0.0415)	(0.0523)	(0.0644)
Num. obs.	926	926	926	926	926	926	926
Parameters	34	34	32	34	34	32	33
Log Likelihood	-267.9106	-269.3701	-272.8983	-271.6257	-272.0020	-278.6894	-272.4048
AIC (Linear model)	628.4554	628.4554	653.8831	628.4554	628.4554	653.8831	653.8831
AIC (Spatial model)	603.8212	606.7402	609.7967	611.2513	612.0041	621.3788	610.8095
LR test: statistic	26.6342	23.7152	46.0864	19.2040	18.4513	34.5043	47.0735
LR test: p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Regression results for the third cluster, that includes Minsk and Kharkov. From left to right: 1) Spatial Lag Model with inverted distance weights matrix; 2) Spatial Lag Model with squared inverted distance weights matrix; 3) Spatial Lag Model without distance to centre regressor; 4) Spatial Error Model with inverted distance weights matrix; 5) Spatial Error Model with squared inverted distance weights matrix; 6) Spatial Error Model without distance to centre regressor 7) Spatial Autoregressive Combined Model without distance to centre regressor

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 8: Regression results for the fourth cluster (Almaty, Kazan, Volgograd, Novosibirsk, Dnepr, Yekaterinburg, Samara, Yerevan, Nizhniy Novgorod, and Tbilisi)

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
(Intercept)	5.2651^{***}	6.1551^{***}	4.7033^{***}	7.2711^{***}	7.2725^{***}	7.2520^{***}	4.1106^{***}
	(0.2179)	(0.1478)	(0.2027)	(0.0736)	(0.0688)	(0.0720)	(0.2440)
Dnepr	−0.1005	−0.0884	−0.1678	−0.0919	−0.0804	−0.2054	−0.1618
	(0.1184)	(0.1187)	(0.1132)	(0.1536)	(0.1359)	(0.1623)	(0.1047)
Yekaterinburg	−0.0169	−0.0211	−0.0332	−0.0347	−0.0307	−0.0824	−0.0239
	(0.0530)	(0.0531)	(0.0446)	(0.0703)	(0.0610)	(0.0660)	(0.0413)
Yerevan	−0.0023	0.0154	−0.0029	0.0300	0.0338	0.0273	−0.0111
	(0.0439)	(0.0439)	(0.0375)	(0.0587)	(0.0506)	(0.0568)	(0.0346)
Kazan	−0.0408	−0.0516	−0.0519	−0.0680	−0.0662	−0.1042	−0.0414
	(0.0477)	(0.0477)	(0.0395)	(0.0634)	(0.0548)	(0.0588)	(0.0366)
N_Novgorod	−0.0525	−0.0528	−0.0511	−0.0633	−0.0568	−0.0800	−0.0464
	(0.0513)	(0.0514)	(0.0435)	(0.0687)	(0.0592)	(0.0657)	(0.0401)
Novosibirsk	−0.0741	−0.0859	−0.0504	−0.1096	−0.1043	−0.1031	−0.0398
	(0.0532)	(0.0532)	(0.0448)	(0.0712)	(0.0614)	(0.0672)	(0.0414)
Samara	-0.2431^{**}	-0.2823^{**}	-0.1968^{**}	-0.3515^{**}	-0.3406^{***}	-0.3165^{**}	-0.1707^{**}

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0875)	(0.0872)	(0.0703)	(0.1168)	(0.1005)	(0.1067)	(0.0651)
Tbilisi	−0.0337	−0.0364	−0.0679	−0.0418	−0.0402	−0.0892	−0.0636
	(0.0415)	(0.0416)	(0.0354)	(0.0552)	(0.0478)	(0.0527)	(0.0327)
Volgograd	-0.1640^{*}	-0.1849^{**}	-0.1810^{**}	-0.2186^{*}	-0.2146^{**}	-0.2576^{**}	-0.1644^{**}
	(0.0687)	(0.0686)	(0.0627)	(0.0919)	(0.0792)	(0.0949)	(0.0580)
dist_walk	0.0148	0.0207	0.0008	0.0202	0.0249	0.0005	−0.0000
	(0.0205)	(0.0206)	(0.0135)	(0.0269)	(0.0236)	(0.0203)	(0.0124)
to_centre	−0.0154	−0.0189		−0.0207	−0.0222		
	(0.0177)	(0.0177)		(0.0233)	(0.0204)		
Air_conditioning	0.1384^{***}	0.1405^{***}	0.1456^{***}	0.1391^{***}	0.1406^{***}	0.1439^{***}	0.1442^{***}
	(0.0127)	(0.0127)	(0.0126)	(0.0128)	(0.0128)	(0.0128)	(0.0125)
Breakfast	-0.0356^{*}	-0.0364^{*}	-0.0373^{*}	-0.0364^{*}	-0.0369^{*}	-0.0382^{*}	-0.0365^{*}
	(0.0166)	(0.0167)	(0.0167)	(0.0168)	(0.0168)	(0.0168)	(0.0165)
Hair_dryer	0.0010	0.0030	0.0107	0.0006	0.0028	0.0070	0.0098
	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0165)	(0.0165)	(0.0163)
Elevator_in_building	0.0914^{***}	0.0926^{***}	0.0679^{***}	0.0957^{***}	0.0963^{***}	0.0801^{***}	0.0656^{***}
	(0.0115)	(0.0115)	(0.0112)	(0.0120)	(0.0119)	(0.0120)	(0.0109)

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
Family_kid_friendly	−0.0027	−0.0022	−0.0011	−0.0036	−0.0032	−0.0026	−0.0002
	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0126)
Free_parking_on_premises	−0.0133	−0.0135	−0.0184	−0.0133	−0.0133	−0.0161	−0.0190
	(0.0111)	(0.0112)	(0.0112)	(0.0112)	(0.0113)	(0.0113)	(0.0111)
Free_parking_on_street	−0.0220	−0.0226*	−0.0229*	−0.0192	−0.0201	−0.0187	−0.0244*
	(0.0113)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0113)
Iron	−0.0314	−0.0315	−0.0335	−0.0296	−0.0303	−0.0303	−0.0339
	(0.0183)	(0.0183)	(0.0184)	(0.0183)	(0.0184)	(0.0183)	(0.0183)
Pets_allowed	−0.0328*	−0.0339*	−0.0280	−0.0310*	−0.0328*	−0.0271	−0.0281
	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)
Self_Check_In	0.0250	0.0251	0.0256	0.0257	0.0253	0.0258	0.0255
	(0.0150)	(0.0151)	(0.0151)	(0.0151)	(0.0152)	(0.0152)	(0.0150)
Smoke_detector	0.0082	0.0087	0.0095	0.0076	0.0083	0.0080	0.0098
	(0.0120)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0120)
Smoking_allowed	−0.0134	−0.0141	−0.0175	−0.0149	−0.0145	−0.0175	−0.0170
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0136)	(0.0136)	(0.0134)
Suitable_for_events	0.0183	0.0159	0.0146	0.0225	0.0182	0.0225	0.0128

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0165)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0166)	(0.0165)
TV	0.1054***	0.1042***	0.1002***	0.1072***	0.1052***	0.1042***	0.0995***
	(0.0174)	(0.0175)	(0.0175)	(0.0175)	(0.0175)	(0.0175)	(0.0173)
Washer	0.0073	0.0063	0.0056	0.0050	0.0039	0.0033	0.0077
	(0.0177)	(0.0177)	(0.0177)	(0.0178)	(0.0178)	(0.0178)	(0.0176)
bathrooms	−0.0388***	−0.0387***	−0.0400***	−0.0401***	−0.0392***	−0.0413***	−0.0392***
	(0.0113)	(0.0113)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0113)
bedrooms	0.1292***	0.1295***	0.1263***	0.1308***	0.1305***	0.1297***	0.1245***
	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)
beds	−0.0545***	−0.0551***	−0.0529***	−0.0541***	−0.0547***	−0.0529***	−0.0526***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
(cancellation_policy)	0.0327**	0.0325**	0.0341**	0.0307*	0.0320**	0.0307*	0.0346**
moderate	(0.0120)	(0.0120)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0120)
(cancellation_policy)	−0.0206	−0.0216	−0.0161	−0.0193	−0.0203	−0.0149	−0.0164
strict	(0.0249)	(0.0249)	(0.0249)	(0.0250)	(0.0251)	(0.0251)	(0.0247)
(cancellation_policy)	0.0349*	0.0345*	0.0319*	0.0360*	0.0347*	0.0353*	0.0311*
strict_14_with_grace_period	(0.0156)	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0158)	(0.0155)

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
min_nights	−0.0082	−0.0082	−0.0094	−0.0085	−0.0083	−0.0095	−0.0093
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
person_capacity	0.0666***	0.0671***	0.0669***	0.0662***	0.0667***	0.0660***	0.0667***
	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0045)	(0.0044)
picture_count	0.0018***	0.0019***	0.0020***	0.0018***	0.0018***	0.0019***	0.0021***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
instant_bookable	0.0160	0.0168	0.0184	0.0143	0.0160	0.0155	0.0184
	(0.0114)	(0.0114)	(0.0114)	(0.0115)	(0.0115)	(0.0115)	(0.0113)
review_rating_value	−0.0050	−0.0056	−0.0051	−0.0046	−0.0055	−0.0042	−0.0050
	(0.0048)	(0.0049)	(0.0049)	(0.0048)	(0.0049)	(0.0048)	(0.0048)
Dnepr:dist_walk	0.0040	0.0009	0.0052	0.0019	−0.0012	0.0018	0.0069
	(0.0412)	(0.0413)	(0.0381)	(0.0531)	(0.0473)	(0.0544)	(0.0352)
Yekaterinburg:dist_walk	−0.0013	−0.0040	−0.0014	−0.0000	−0.0041	−0.0015	−0.0007
	(0.0259)	(0.0259)	(0.0197)	(0.0338)	(0.0298)	(0.0289)	(0.0182)
Yerevan:dist_walk	−0.0165	−0.0188	−0.0147	−0.0152	−0.0178	−0.0310	−0.0105
	(0.0273)	(0.0273)	(0.0170)	(0.0354)	(0.0314)	(0.0253)	(0.0157)
Kazan:dist_walk	−0.0254	−0.0303	−0.0147	−0.0287	−0.0334	−0.0144	−0.0139

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
	(0.0215)	(0.0215)	(0.0148)	(0.0282)	(0.0247)	(0.0222)	(0.0136)
N_Novgorod:dist_walk	−0.0054	−0.0112	0.0053	−0.0091	−0.0147	0.0030	0.0068
	(0.0226)	(0.0226)	(0.0157)	(0.0297)	(0.0260)	(0.0238)	(0.0145)
Novosibirsk:dist_walk	−0.0359	−0.0387	−0.0289	−0.0491	−0.0448	−0.0498	−0.0240
	(0.0305)	(0.0306)	(0.0205)	(0.0393)	(0.0348)	(0.0303)	(0.0190)
Samara:dist_walk	−0.0169	−0.0250	−0.0011	−0.0283	−0.0321	−0.0037	0.0001
	(0.0313)	(0.0313)	(0.0220)	(0.0412)	(0.0360)	(0.0332)	(0.0202)
Tbilisi:dist_walk	0.0003	−0.0029	−0.0192	−0.0075	−0.0067	−0.0279	−0.0162
	(0.0232)	(0.0232)	(0.0168)	(0.0300)	(0.0266)	(0.0243)	(0.0155)
Volgograd:dist_walk	0.0305	0.0293	0.0105	0.0325	0.0301	0.0089	0.0118
	(0.0358)	(0.0358)	(0.0289)	(0.0470)	(0.0412)	(0.0430)	(0.0266)
Dnepr:to_centre	-0.1053^{*}	-0.1328^{**}		-0.1561^{*}	-0.1633^{**}		
	(0.0467)	(0.0466)		(0.0610)	(0.0535)		
Yekaterinburg:to_centre	−0.0122	−0.0145		−0.0210	−0.0191		
	(0.0215)	(0.0216)		(0.0285)	(0.0248)		
Yerevan:to_centre	−0.0037	−0.0107		−0.0239	−0.0225		
	(0.0258)	(0.0258)		(0.0335)	(0.0296)		

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
Kazan:to_centre	0.0007	0.0021		−0.0003	0.0021		
	(0.0187)	(0.0187)		(0.0247)	(0.0216)		
N_Novgorod:to_centre	0.0064	0.0074		0.0050	0.0068		
	(0.0194)	(0.0194)		(0.0256)	(0.0224)		
Novosibirsk:to_centre	0.0069	0.0047		0.0051	0.0029		
	(0.0231)	(0.0232)		(0.0303)	(0.0266)		
Samara:to_centre	0.0157	0.0202		0.0252	0.0254		
	(0.0247)	(0.0247)		(0.0327)	(0.0285)		
Tbilisi:to_centre	−0.0209	−0.0220		−0.0244	−0.0241		
	(0.0182)	(0.0183)		(0.0241)	(0.0210)		
Volgograd:to_centre	−0.0249	−0.0260		−0.0291	−0.0284		
	(0.0241)	(0.0241)		(0.0320)	(0.0278)		
ρ	0.2598^{***}	0.1448^{***}	0.3317^{***}				0.4089^{***}
	(0.0270)	(0.0173)	(0.0253)				(0.0310)
λ				0.2596^{***}	0.1349^{***}	0.3510^{***}	-0.0841^{**}
				(0.0297)	(0.0187)	(0.0275)	(0.0262)
Num. obs.	6404	6404	6404	6404	6404	6404	6404

Table8 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center	SAC without distance to center
Parameters	58	58	48	58	58	48	49
Log Likelihood	-3208.7353	-3220.1518	-3250.1523	-3218.5508	-3230.3130	-3259.0853	-3246.0609
AIC (Linear model)	6626.9755	6626.9755	6773.0479	6626.9755	6626.9755	6773.0479	6773.0479
AIC (Spatial model)	6533.4705	6556.3037	6596.3047	6553.1015	6576.6261	6614.1705	6590.1219
LR test: statistic	95.5050	72.6718	178.7432	75.8740	52.3494	160.8774	186.9260
LR test: p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Regression results for the fourth cluster, that includes Almaty, Kazan, Volgograd, Novosibirsk, Dnepr, Yekaterinburg, Samara, Yerevan, Nizhniy Novgorod, Tbilisi. From left to right: 1) Spatial Lag Model with inverted distance weights matrix 2) Spatial Lag Model with squared inverted distance weights matrix 3) Spatial Lag Model without distance to centre regressor 4) Spatial Error Model with inverted distance weights matrix 5) Spatial Error Model with squared inverted distance weights matrix 6) Spatial Error Model without distance to centre regressor 7) Spatial Autoregressive Combined Model without distance to centre regressor

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 9: Regression results for all cities

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
(Intercept)	5.0438^{***}	5.8541^{***}	4.5083^{***}	7.2520^{***}	7.2521^{***}	7.2301^{***}
	(0.1252)	(0.0914)	(0.1146)	(0.0605)	(0.0548)	(0.0579)
(city)Baku	-0.1703^{*}	-0.1980^{**}	-0.1600^{*}	-0.2657^{*}	-0.2573^{**}	-0.2817^{**}
	(0.0769)	(0.0768)	(0.0643)	(0.1059)	(0.0926)	(0.0957)
(city)Dnepr	−0.1194	−0.1078	−0.1797	−0.1133	−0.0998	−0.2242
	(0.1132)	(0.1133)	(0.1081)	(0.1526)	(0.1361)	(0.1592)
(city)Ekaterinburg	−0.0421	−0.0461	−0.0521	−0.0621	−0.0585	−0.1037
	(0.0499)	(0.0499)	(0.0416)	(0.0696)	(0.0605)	(0.0644)
(city)Erevan	−0.0037	0.0129	−0.0042	0.0310	0.0347	0.0266
	(0.0417)	(0.0417)	(0.0356)	(0.0586)	(0.0507)	(0.0559)
(city)Kazan	−0.0613	−0.0716	−0.0668	−0.0919	−0.0913	-0.1224^{*}
	(0.0449)	(0.0450)	(0.0369)	(0.0629)	(0.0545)	(0.0574)
(city)Kharkov	-0.1339^{*}	-0.1480^{**}	-0.1539^{**}	-0.1608^{*}	-0.1656^{*}	-0.2171^{**}
	(0.0555)	(0.0555)	(0.0493)	(0.0762)	(0.0669)	(0.0728)
(city)Kiev	0.0733	0.1003^{**}	0.0313	0.1439^{**}	0.1451^{**}	0.0922
	(0.0386)	(0.0385)	(0.0325)	(0.0539)	(0.0467)	(0.0509)

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
(city)Minsk	-0.0337	-0.0392	-0.0475	-0.0646	-0.0569	-0.1021
	(0.0453)	(0.0453)	(0.0372)	(0.0634)	(0.0550)	(0.0582)
(city)Moscow	0.1500^{***}	0.1765^{***}	0.1228^{***}	0.2191^{***}	0.2214^{***}	0.1764^{***}
	(0.0387)	(0.0386)	(0.0322)	(0.0540)	(0.0468)	(0.0503)
(city)N_Novgorod	-0.0674	-0.0682	-0.0627	-0.0798	-0.0745	-0.0938
	(0.0485)	(0.0486)	(0.0409)	(0.0683)	(0.0591)	(0.0643)
(city)Novosibirsk	-0.0928	-0.1041^{*}	-0.0647	-0.1325	-0.1284^{*}	-0.1195
	(0.0504)	(0.0504)	(0.0422)	(0.0709)	(0.0613)	(0.0659)
(city)Saint_Petersburg	-0.0750	-0.1032^{**}	-0.0674^{*}	-0.1588^{**}	-0.1547^{***}	-0.1753^{***}
	(0.0390)	(0.0389)	(0.0328)	(0.0542)	(0.0470)	(0.0508)
(city)Samara	-0.2508^{**}	-0.2869^{***}	-0.2009^{**}	-0.3712^{**}	-0.3617^{***}	-0.3262^{**}
	(0.0830)	(0.0830)	(0.0666)	(0.1167)	(0.1009)	(0.1051)
(city)Tbilisi	-0.0443	-0.0469	-0.0699^{*}	-0.0555	-0.0540	-0.0957
	(0.0391)	(0.0391)	(0.0332)	(0.0547)	(0.0474)	(0.0515)
(city)Volgograd	-0.1749^{**}	-0.1938^{**}	-0.1904^{**}	-0.2339^{*}	-0.2308^{**}	-0.2711^{**}
	(0.0652)	(0.0652)	(0.0595)	(0.0917)	(0.0793)	(0.0934)
dist_walk	0.0156	0.0210	0.0018	0.0209	0.0260	0.0014

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
	(0.0196)	(0.0196)	(0.0129)	(0.0268)	(0.0237)	(0.0200)
to_centre	−0.0153	−0.0186		−0.0209	−0.0227	
	(0.0169)	(0.0170)		(0.0233)	(0.0205)	
Air_conditioning	0.1139***	0.1153***	0.1230***	0.1142***	0.1155***	0.1216***
	(0.0077)	(0.0077)	(0.0077)	(0.0078)	(0.0078)	(0.0078)
Breakfast	−0.0520***	−0.0518***	−0.0502***	−0.0526***	−0.0522***	−0.0513***
	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0103)
Hair_dryer	−0.0031	−0.0007	0.0046	−0.0053	−0.0021	0.0001
	(0.0106)	(0.0106)	(0.0106)	(0.0107)	(0.0107)	(0.0107)
Elevator_in_building	0.0597***	0.0603***	0.0399***	0.0625***	0.0628***	0.0476***
	(0.0067)	(0.0067)	(0.0064)	(0.0070)	(0.0070)	(0.0070)
Family_kid_friendly	0.0124	0.0123	0.0129	0.0129	0.0123	0.0135
	(0.0070)	(0.0070)	(0.0070)	(0.0070)	(0.0070)	(0.0071)
Free_parking_on_premises	−0.0131*	−0.0139*	−0.0213***	−0.0122	−0.0129*	−0.0185**
	(0.0063)	(0.0063)	(0.0063)	(0.0064)	(0.0064)	(0.0064)
Free_parking_on_street	−0.0221***	−0.0236***	−0.0256***	−0.0195**	−0.0214**	−0.0219***
	(0.0066)	(0.0066)	(0.0065)	(0.0066)	(0.0066)	(0.0066)

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
Iron	-0.0090	-0.0101	-0.0112	-0.0078	-0.0096	-0.0090
	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)
Pets_allowed	-0.0100	-0.0100	-0.0099	-0.0104	-0.0105	-0.0109
	(0.0085)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)
Self_Check_In	0.0089	0.0089	0.0114	0.0076	0.0075	0.0089
	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0086)	(0.0087)
Smoke_detector	0.0250^{***}	0.0250^{***}	0.0221^{**}	0.0237^{***}	0.0233^{***}	0.0215^{**}
	(0.0069)	(0.0069)	(0.0069)	(0.0070)	(0.0070)	(0.0070)
Smoking_allowed	-0.0229^{*}	-0.0243^{**}	-0.0250^{**}	-0.0212^{*}	-0.0222^{*}	-0.0216^{*}
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)
Suitable_for_events	0.0066	0.0051	0.0062	0.0091	0.0062	0.0098
	(0.0118)	(0.0118)	(0.0119)	(0.0119)	(0.0119)	(0.0119)
TV	0.1480^{***}	0.1474^{***}	0.1430^{***}	0.1499^{***}	0.1493^{***}	0.1460^{***}
	(0.0099)	(0.0099)	(0.0099)	(0.0100)	(0.0100)	(0.0100)
Washer	-0.0231^{*}	-0.0229^{*}	-0.0230^{*}	-0.0230^{*}	-0.0222	-0.0223
	(0.0116)	(0.0116)	(0.0117)	(0.0117)	(0.0118)	(0.0118)
bathrooms	-0.0464^{***}	-0.0463^{***}	-0.0465^{***}	-0.0489^{***}	-0.0484^{***}	-0.0493^{***}

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0072)
bedrooms	0.0994^{***}	0.0993^{***}	0.0977^{***}	0.0997^{***}	0.0996^{***}	0.0987^{***}
	(0.0052)	(0.0052)	(0.0052)	(0.0053)	(0.0053)	(0.0053)
beds	-0.0611^{***}	-0.0616^{***}	-0.0615^{***}	-0.0600^{***}	-0.0606^{***}	-0.0603^{***}
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
(cancellation_policy)moderate	0.0310^{***}	0.0308^{***}	0.0347^{***}	0.0304^{***}	0.0308^{***}	0.0332^{***}
	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)
(cancellation_policy)strict	0.0234^{*}	0.0247^{*}	0.0340^{**}	0.0223^{*}	0.0245^{*}	0.0300^{**}
	(0.0107)	(0.0107)	(0.0107)	(0.0108)	(0.0109)	(0.0109)
(cancellation_policy)	0.0326^{***}	0.0327^{***}	0.0365^{***}	0.0338^{***}	0.0336^{***}	0.0381^{***}
strict_14_with_grace_period	(0.0089)	(0.0089)	(0.0088)	(0.0089)	(0.0089)	(0.0090)
min_nights	-0.0124^{***}	-0.0126^{***}	-0.0126^{***}	-0.0126^{***}	-0.0127^{***}	-0.0128^{***}
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
person_capacity	0.0795^{***}	0.0800^{***}	0.0811^{***}	0.0795^{***}	0.0799^{***}	0.0808^{***}
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0030)
picture_count	0.0023^{***}	0.0023^{***}	0.0025^{***}	0.0022^{***}	0.0023^{***}	0.0024^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
instant_bookable	0.0252^{***}	0.0266^{***}	0.0282^{***}	0.0245^{***}	0.0263^{***}	0.0272^{***}
	(0.0065)	(0.0065)	(0.0065)	(0.0066)	(0.0066)	(0.0066)
review_rating_value	−0.0025	−0.0031	−0.0028	−0.0025	−0.0032	−0.0026
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
(city)Baku:dist_walk	−0.0478	−0.0593	−0.0347	−0.0525	−0.0676	−0.0305
	(0.0517)	(0.0517)	(0.0474)	(0.0670)	(0.0607)	(0.0665)
(city)Dnepr:dist_walk	0.0023	−0.0007	0.0042	0.0013	−0.0026	0.0018
	(0.0395)	(0.0395)	(0.0364)	(0.0527)	(0.0473)	(0.0533)
(city)Ekaterinburg:dist_walk	−0.0041	−0.0066	−0.0035	−0.0029	−0.0067	−0.0041
	(0.0248)	(0.0248)	(0.0188)	(0.0336)	(0.0298)	(0.0284)
(city)Erevan:dist_walk	−0.0138	−0.0164	−0.0119	−0.0112	−0.0148	−0.0291
	(0.0261)	(0.0261)	(0.0162)	(0.0351)	(0.0314)	(0.0249)
(city)Kazan:dist_walk	−0.0256	−0.0301	−0.0146	−0.0285	−0.0334	−0.0138
	(0.0205)	(0.0205)	(0.0141)	(0.0280)	(0.0248)	(0.0218)
(city)Kharkov:dist_walk	−0.0074	−0.0016	−0.0346	−0.0258	−0.0101	−0.0645
	(0.0490)	(0.0490)	(0.0437)	(0.0602)	(0.0565)	(0.0576)
(city)Kiev:dist_walk	−0.0170	−0.0218	-0.0382^{**}	−0.0292	−0.0298	-0.0733^{**}

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
	(0.0214)	(0.0214)	(0.0147)	(0.0291)	(0.0258)	(0.0227)
(city)Minsk:dist_walk	−0.0133	−0.0193	−0.0130	−0.0219	−0.0265	−0.0246
	(0.0227)	(0.0228)	(0.0159)	(0.0311)	(0.0275)	(0.0246)
(city)Moscow:dist_walk	−0.0128	−0.0165	−0.0096	−0.0149	−0.0192	−0.0184
	(0.0201)	(0.0201)	(0.0133)	(0.0274)	(0.0243)	(0.0207)
(city)N_Novgorod:dist_walk	−0.0060	−0.0114	0.0047	−0.0091	−0.0151	0.0027
	(0.0216)	(0.0216)	(0.0150)	(0.0296)	(0.0261)	(0.0234)
(city)Novosibirsk:dist_walk	−0.0367	−0.0397	−0.0283	−0.0526	−0.0482	−0.0514
	(0.0292)	(0.0292)	(0.0196)	(0.0389)	(0.0348)	(0.0297)
(city)Saint_Petersburg:dist_walk	−0.0089	−0.0141	−0.0058	−0.0125	−0.0180	−0.0072
	(0.0204)	(0.0204)	(0.0137)	(0.0278)	(0.0246)	(0.0212)
(city)Samara:dist_walk	−0.0202	−0.0274	−0.0031	−0.0328	−0.0363	−0.0061
	(0.0299)	(0.0299)	(0.0210)	(0.0410)	(0.0361)	(0.0327)
(city)Tbilisi:dist_walk	−0.0003	−0.0034	−0.0153	−0.0088	−0.0082	−0.0246
	(0.0222)	(0.0222)	(0.0160)	(0.0298)	(0.0266)	(0.0238)
(city)Volgograd:dist_walk	0.0358	0.0345	0.0173	0.0386	0.0358	0.0166
	(0.0342)	(0.0342)	(0.0276)	(0.0468)	(0.0412)	(0.0422)

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
(city)Baku:to_centre	0.0042	0.0072		0.0069	0.0106	
	(0.0279)	(0.0279)		(0.0386)	(0.0339)	
(city)Dnepr:to_centre	-0.0978^{*}	-0.1225^{**}		-0.1531^{*}	-0.1607^{**}	
	(0.0444)	(0.0444)		(0.0607)	(0.0536)	
(city)Ekaterinburg:to_centre	−0.0097	−0.0119		−0.0192	−0.0175	
	(0.0206)	(0.0206)		(0.0284)	(0.0249)	
(city)Erevan:to_centre	−0.0037	−0.0097		−0.0269	−0.0244	
	(0.0246)	(0.0246)		(0.0333)	(0.0296)	
(city)Kazan:to_centre	0.0024	0.0039		0.0012	0.0039	
	(0.0179)	(0.0179)		(0.0246)	(0.0216)	
(city)Kharkov:to_centre	−0.0202	−0.0255		−0.0327	−0.0338	
	(0.0214)	(0.0214)		(0.0293)	(0.0258)	
(city)Kiev:to_centre	−0.0148	−0.0184		−0.0266	−0.0256	
	(0.0173)	(0.0173)		(0.0237)	(0.0209)	
(city)Minsk:to_centre	−0.0026	−0.0027		−0.0044	−0.0035	
	(0.0183)	(0.0183)		(0.0252)	(0.0221)	
(city)Moscow:to_centre	0.0080	0.0092		0.0075	0.0092	

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
	(0.0170)	(0.0170)		(0.0233)	(0.0205)	
(city)N_Novgorod:to_centre	0.0066	0.0079		0.0048	0.0071	
	(0.0186)	(0.0186)		(0.0256)	(0.0224)	
(city)Novosibirsk:to_centre	0.0082	0.0065		0.0069	0.0049	
	(0.0221)	(0.0221)		(0.0302)	(0.0266)	
(city)Saint_Petersburg:to_centre	0.0068	0.0095		0.0101	0.0120	
	(0.0170)	(0.0170)		(0.0234)	(0.0206)	
(city)Samara:to_centre	0.0172	0.0213		0.0280	0.0282	
	(0.0236)	(0.0236)		(0.0326)	(0.0286)	
(city)Tbilisi:to_centre	−0.0161	−0.0168		−0.0198	−0.0193	
	(0.0174)	(0.0175)		(0.0240)	(0.0211)	
(city)Volgograd:to_centre	−0.0233	−0.0241		−0.0280	−0.0270	
	(0.0230)	(0.0231)		(0.0319)	(0.0279)	
ρ	0.2856^{***}	0.1810^{***}	0.3534^{***}			
	(0.0150)	(0.0101)	(0.0138)			
λ				0.2918^{***}	0.1782^{***}	0.3705^{***}
				(0.0162)	(0.0108)	(0.0151)

Table9 – continued from previous page

	SLM	SLM other weights	SLM without distance to center	SEM	SEM other weights	SEM without distance to center
Num. obs.	17057	17057	17057	17057	17057	17057
Parameters	76	76	60	76	76	60
Log Likelihood	-7835.5524	-7850.5493	-7926.8565	-7863.2184	-7879.4909	-7978.4857
AIC (Linear model)	16176.8711	16176.8711	16615.3548	16176.8711	16176.8711	16615.3548
AIC (Spatial model)	15823.1048	15853.0987	15973.7130	15878.4367	15910.9818	16076.9714
LR test: statistic	355.7663	325.7725	643.6418	300.4344	267.8894	540.3834
LR test: p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Regression results for all cities. From left to right: 1) Spatial Lag Model with inverted distance weights matrix 2) Spatial Lag Model with squared inverted distance weights matrix 3) Spatial Lag Model without distance to centre regressor 4) Spatial Error Model with inverted distance weights matrix 5) Spatial Error Model with squared inverted distance weights matrix 6) Spatial Error Model without distance to centre regressor

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Figure 1: Cities with subway or light rail in the former Soviet Union countries

Figure 2: The number of observation for each city

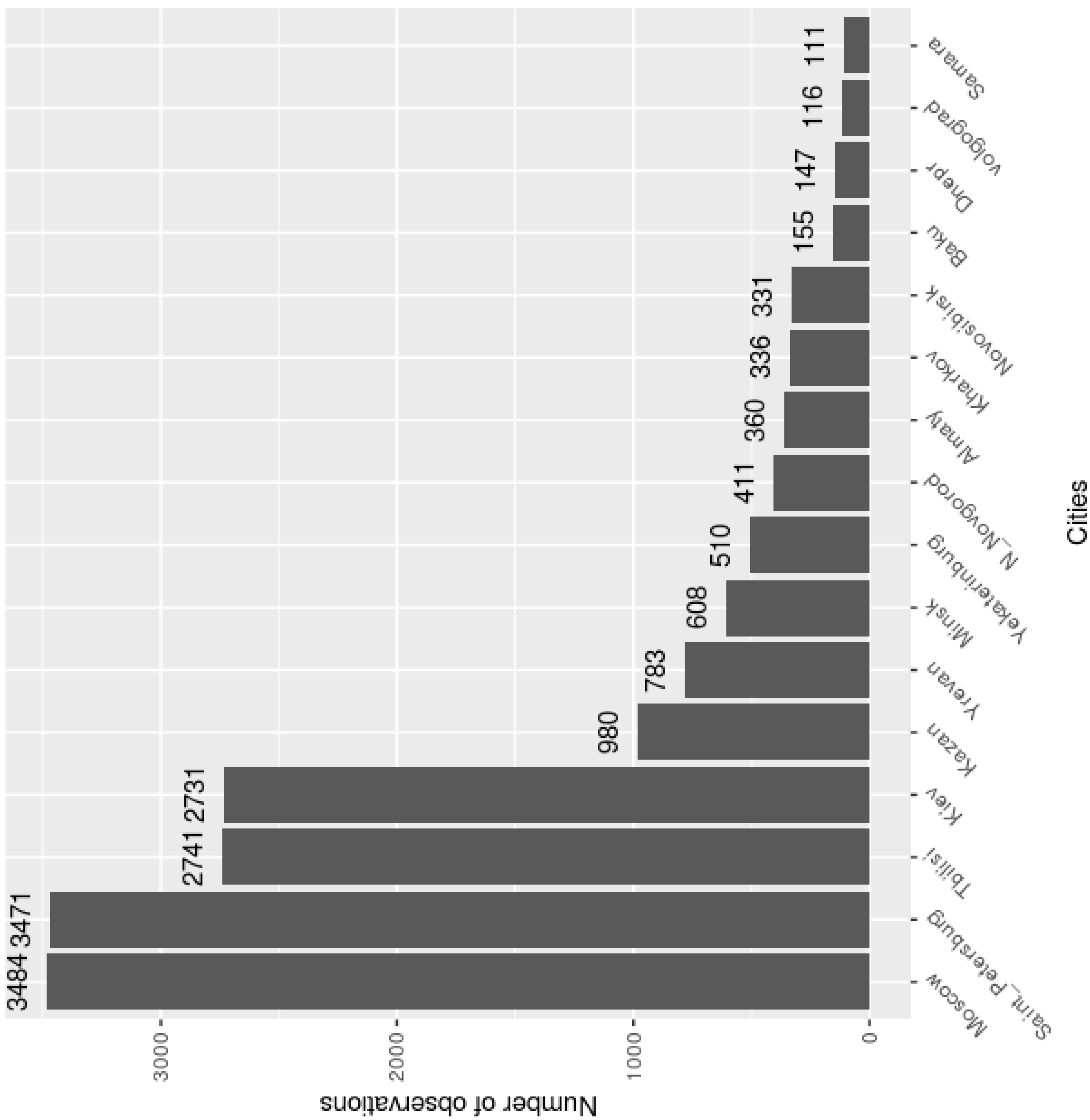

Figure 3: Almaty: Republic Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

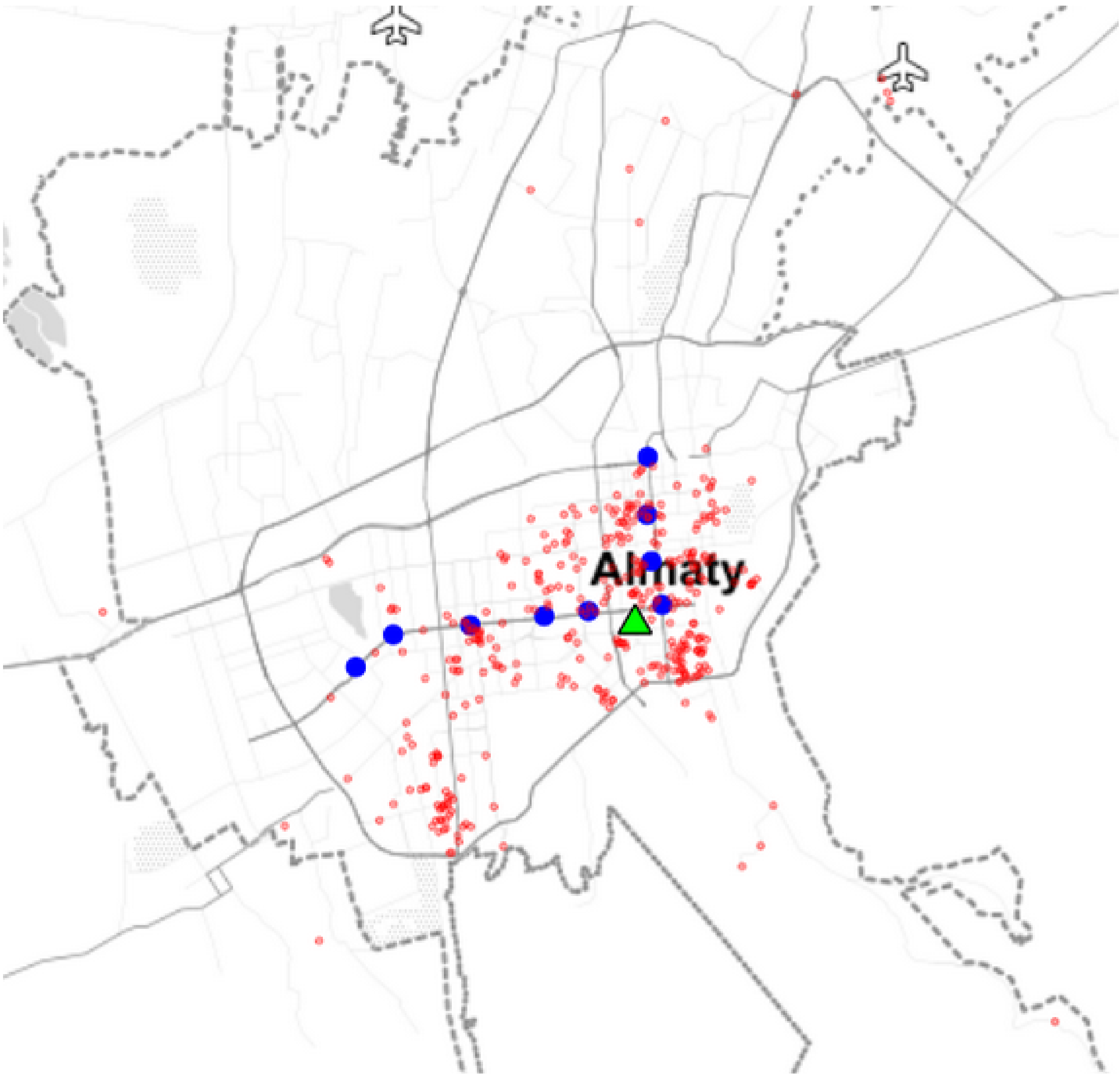

Figure 4: Baku: Azadliq Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

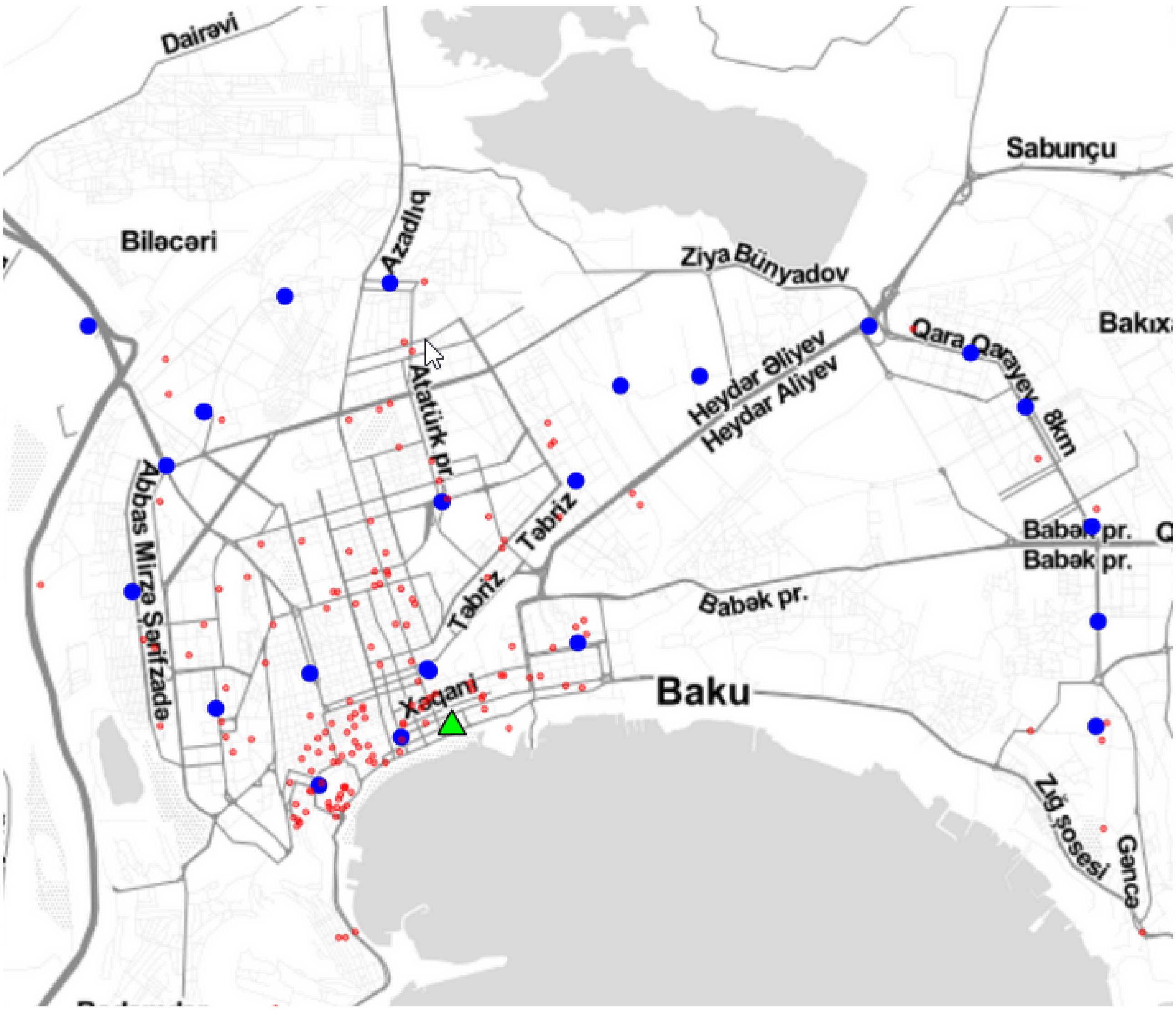

Figure 5: Dnepr: Cathedral Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

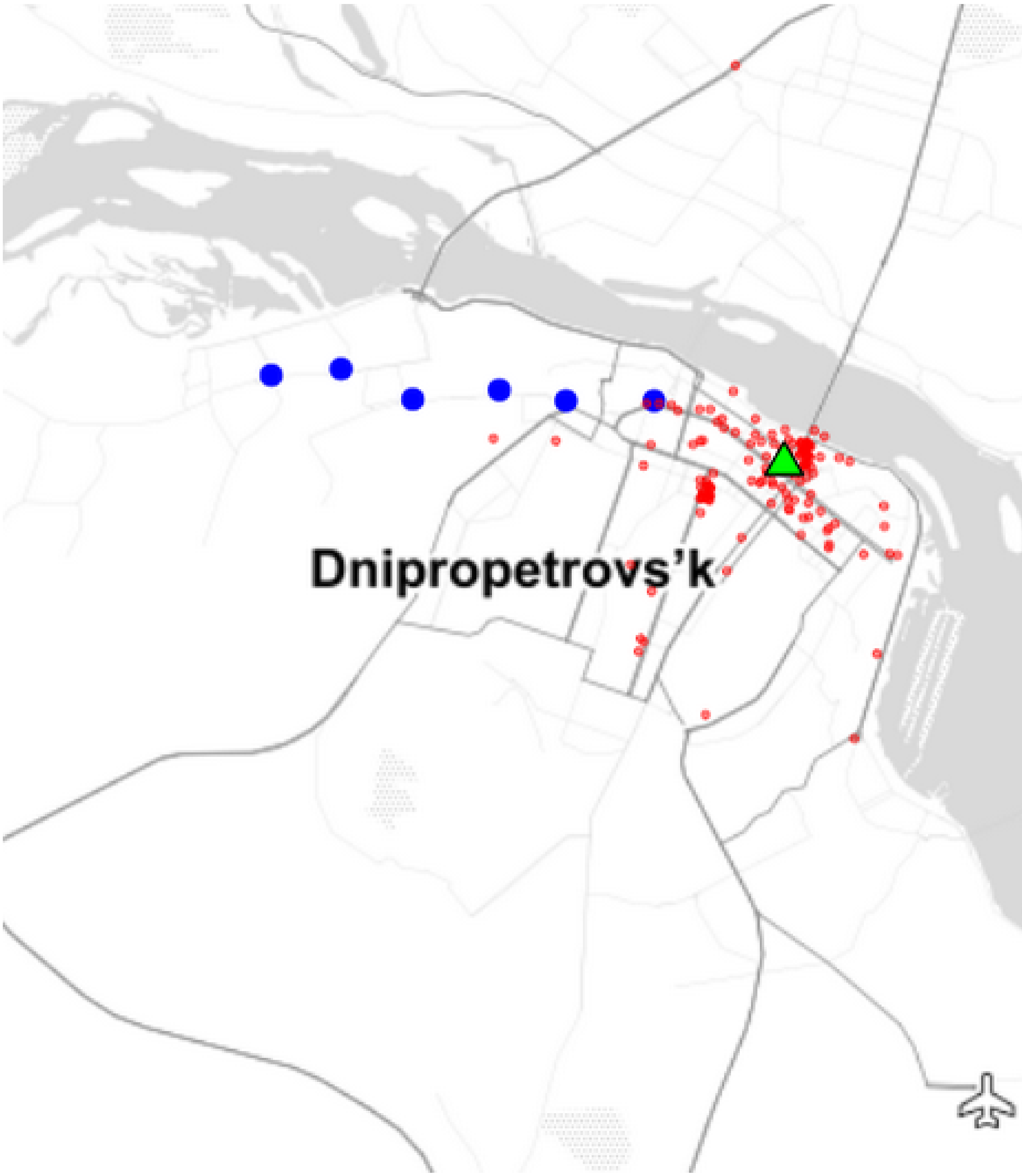

Figure 6: Kazan: Tukai Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

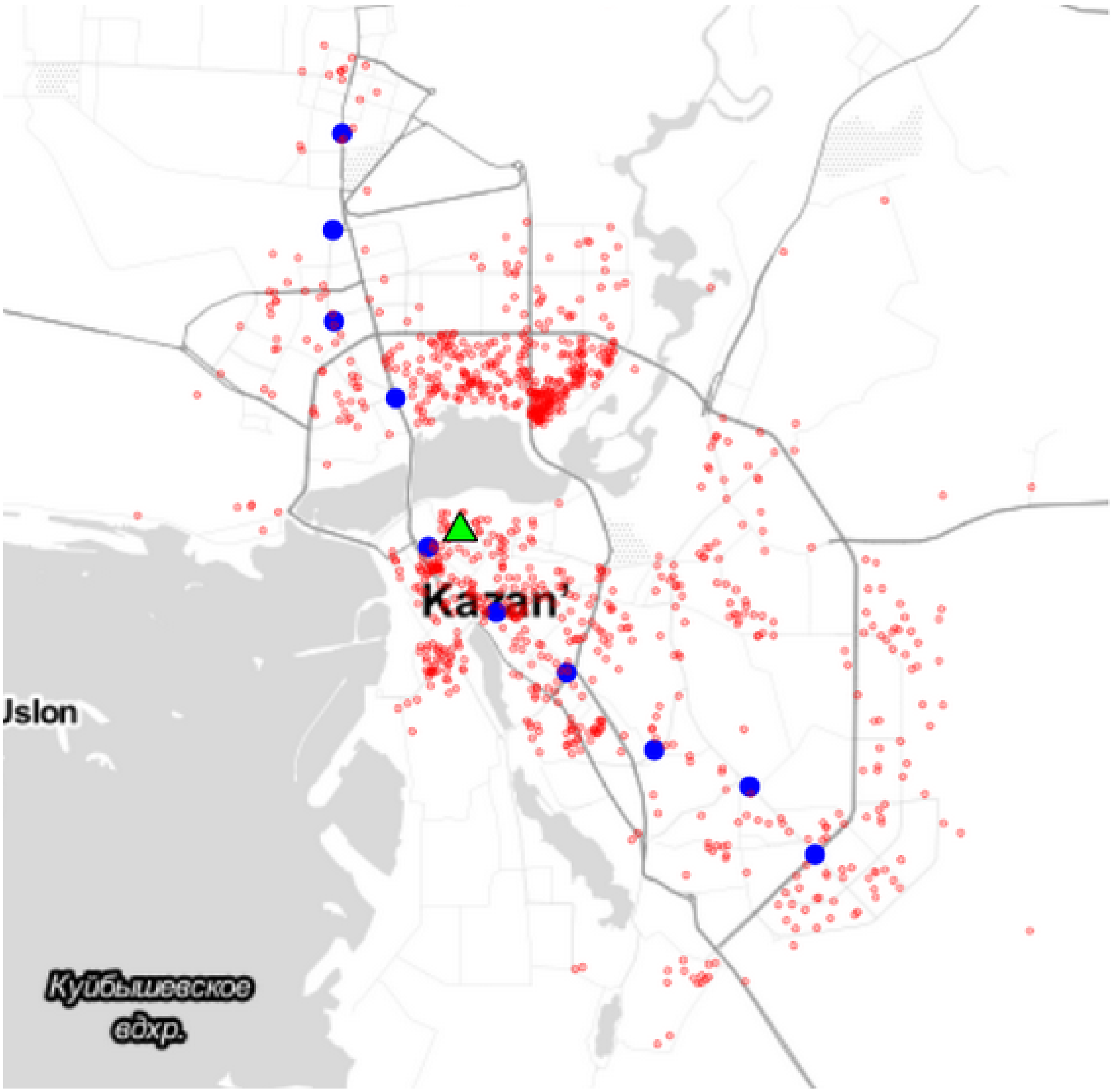

Figure 7: Kharkov: Freedom Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

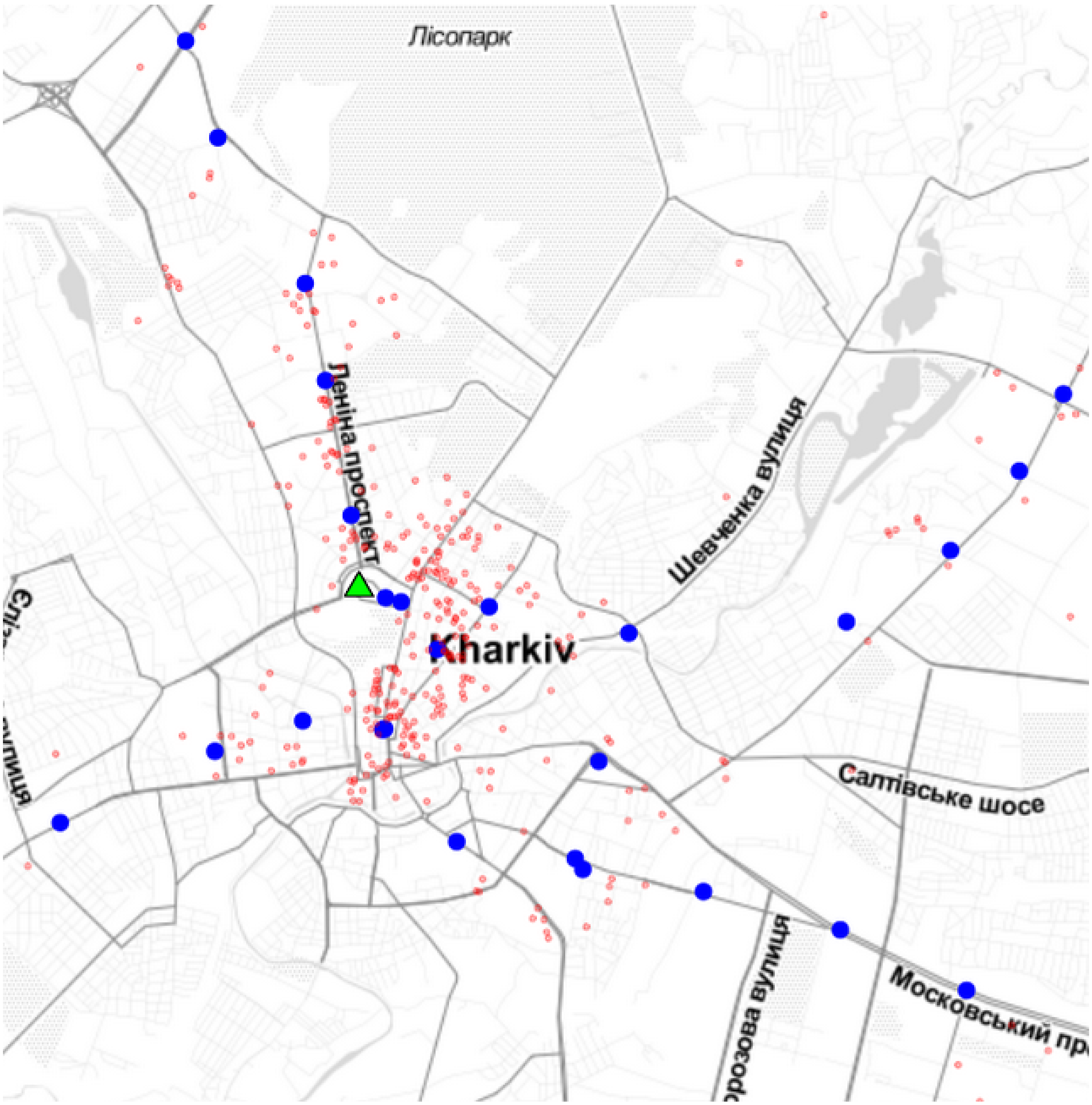

Figure 8: Kiev: Independence Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

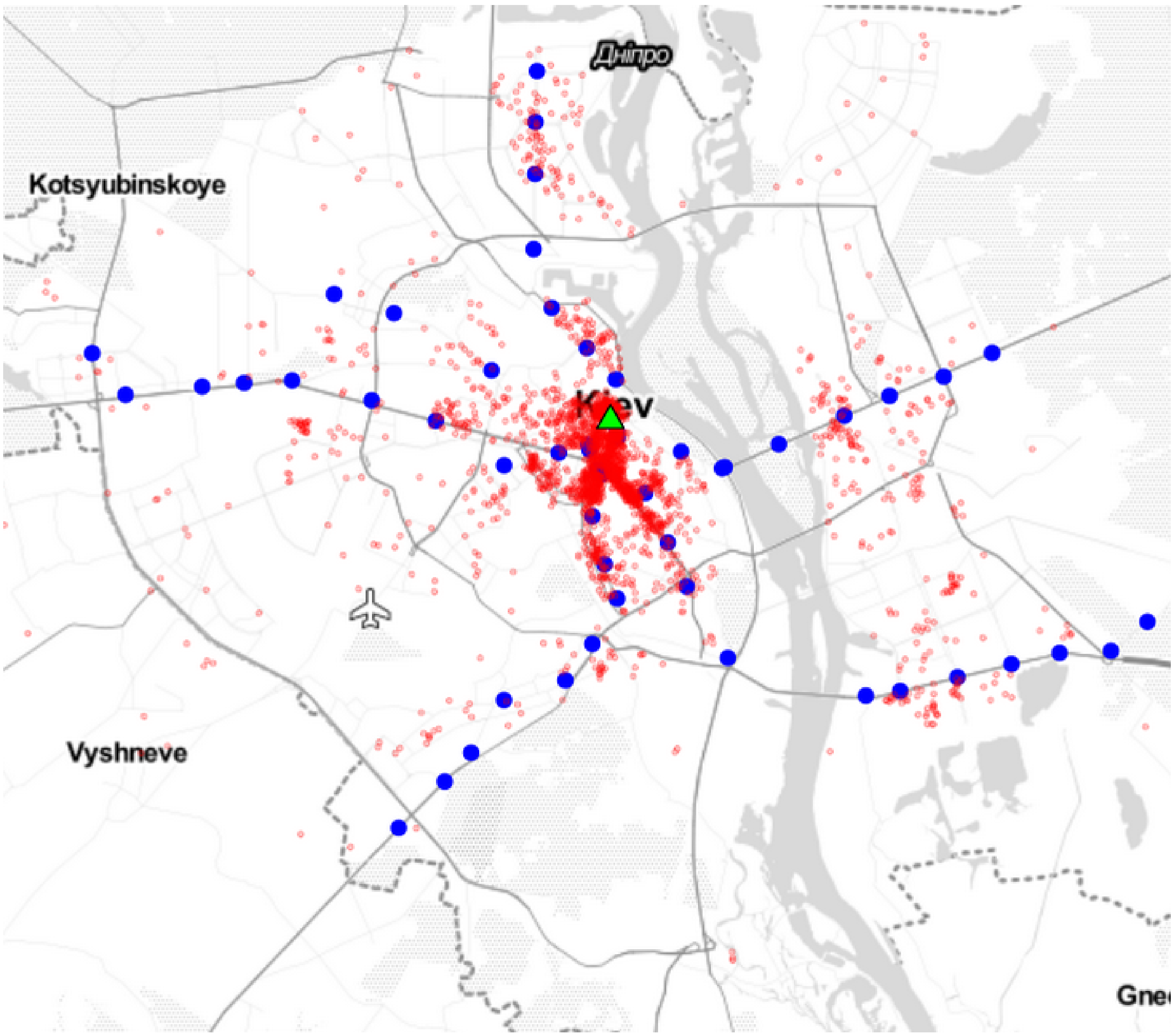

Figure 9: Minsk: Independence Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

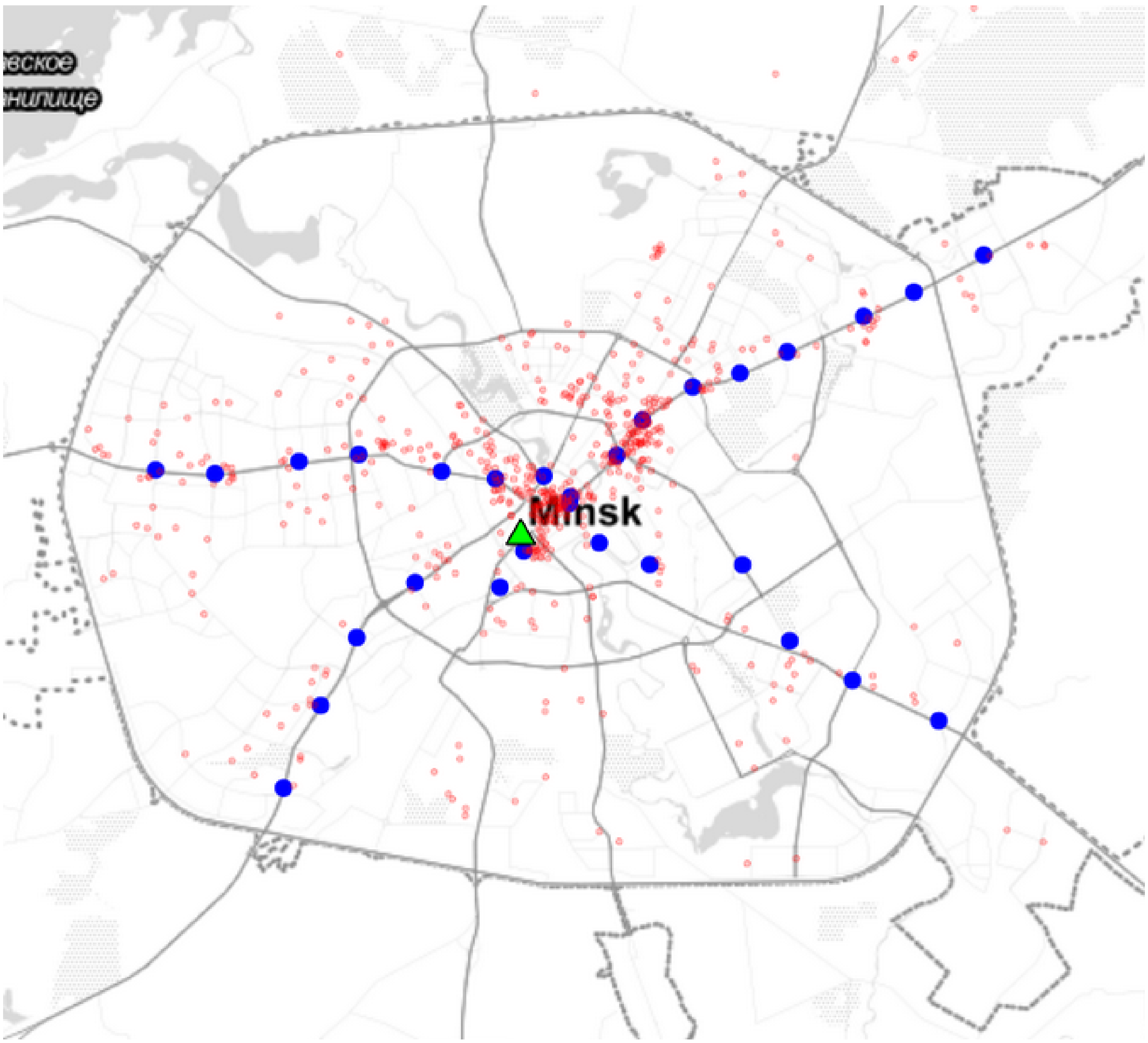

Figure 10: Moscow: The Red Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

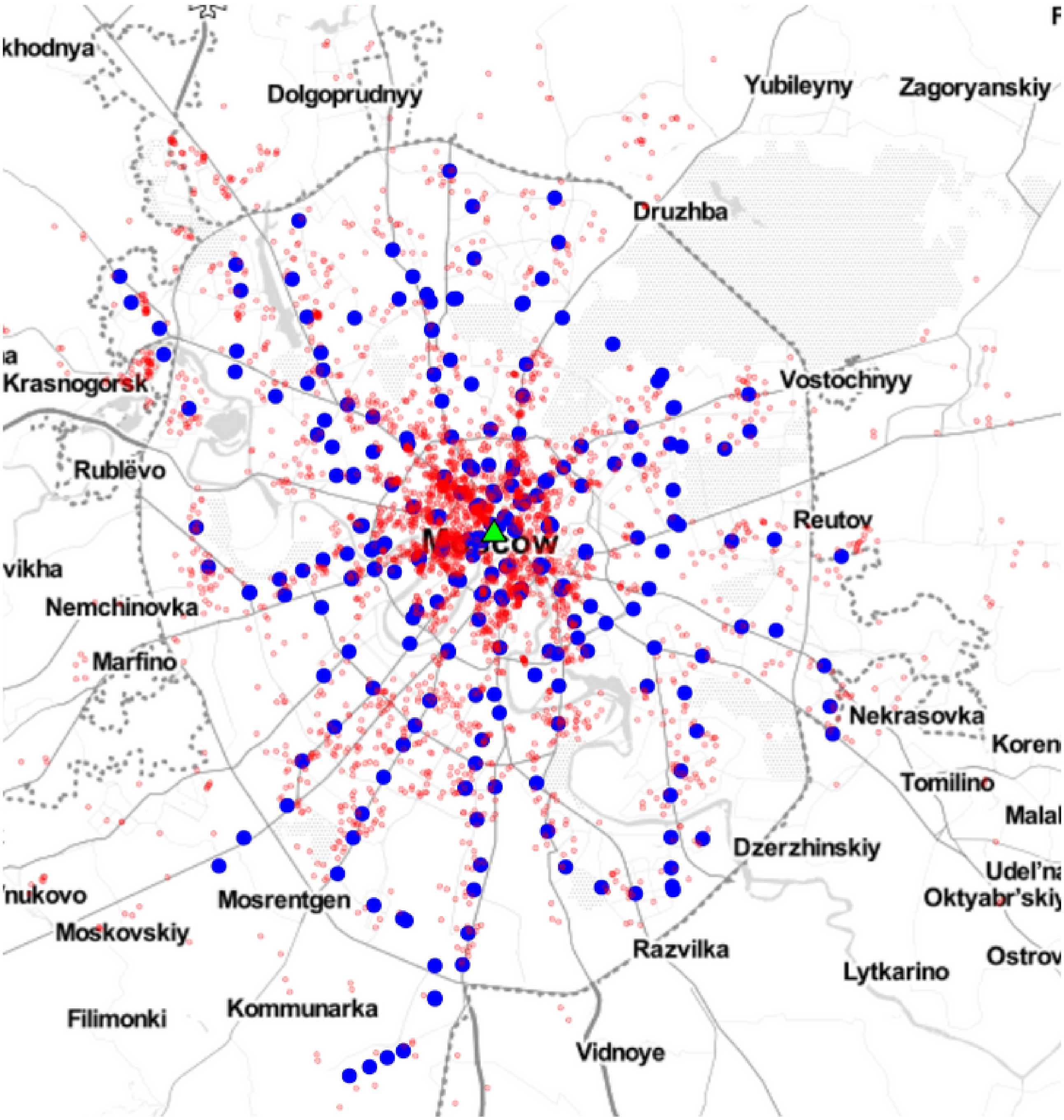

Figure 11: Nizhniy Novgorod: The Minin and Pozharsky Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

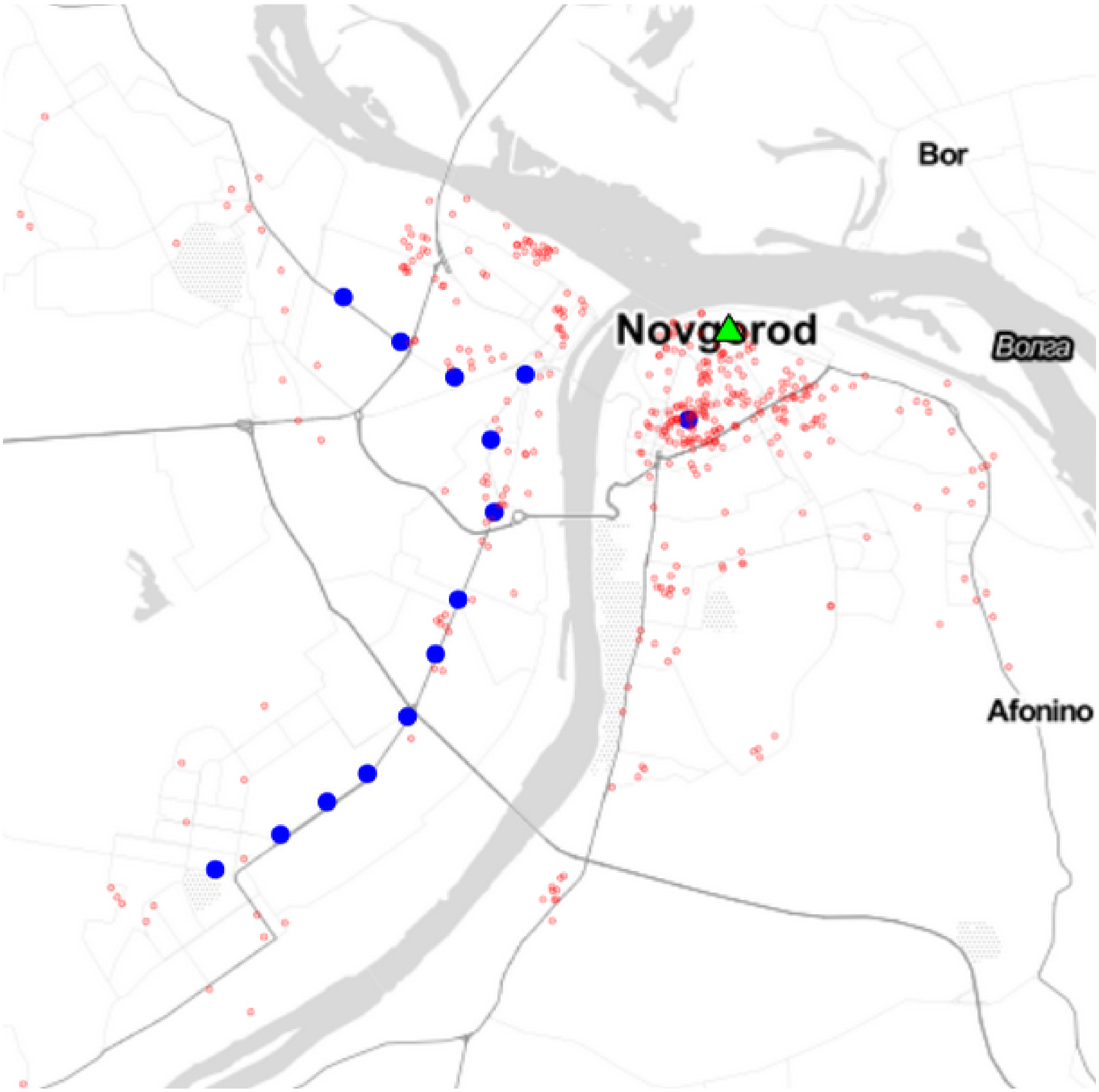

Figure 12: Novosibirsk: The Lenin Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

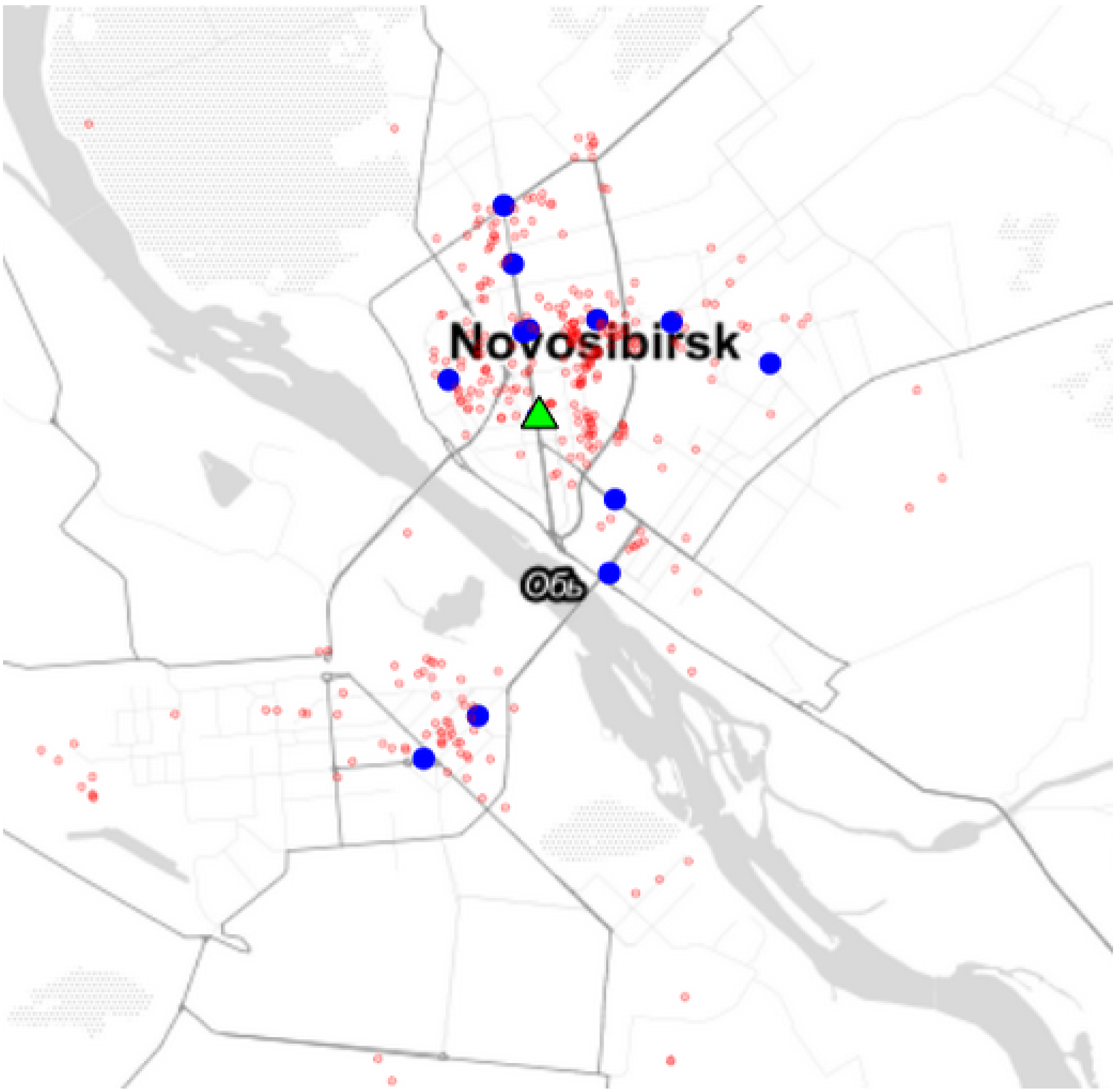

Figure 13: Samara: The Kuybyishev Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

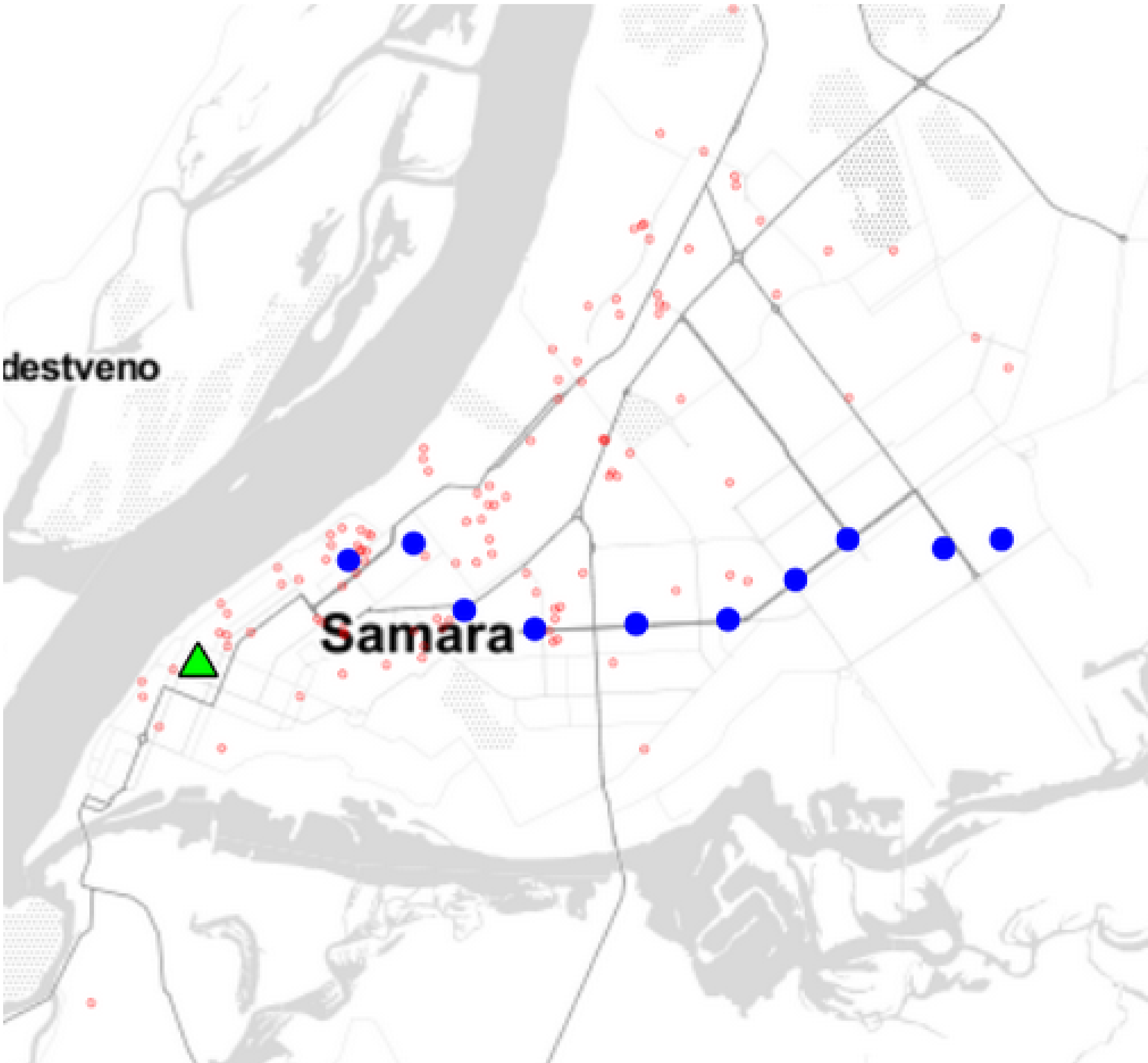

Figure 14: St. Petersburg: The Palace Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

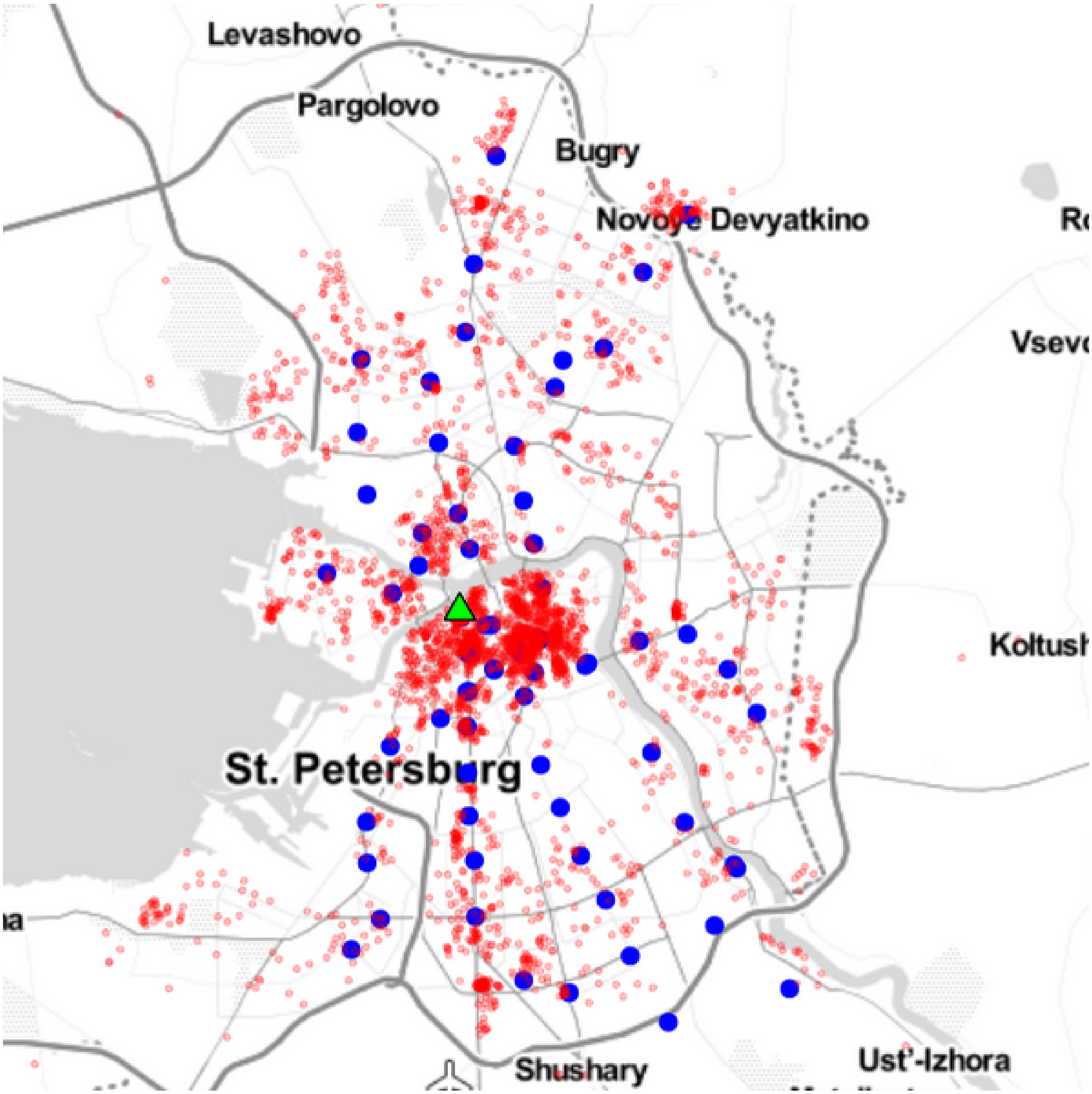

Figure 15: Tbilisi: The Freedom Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

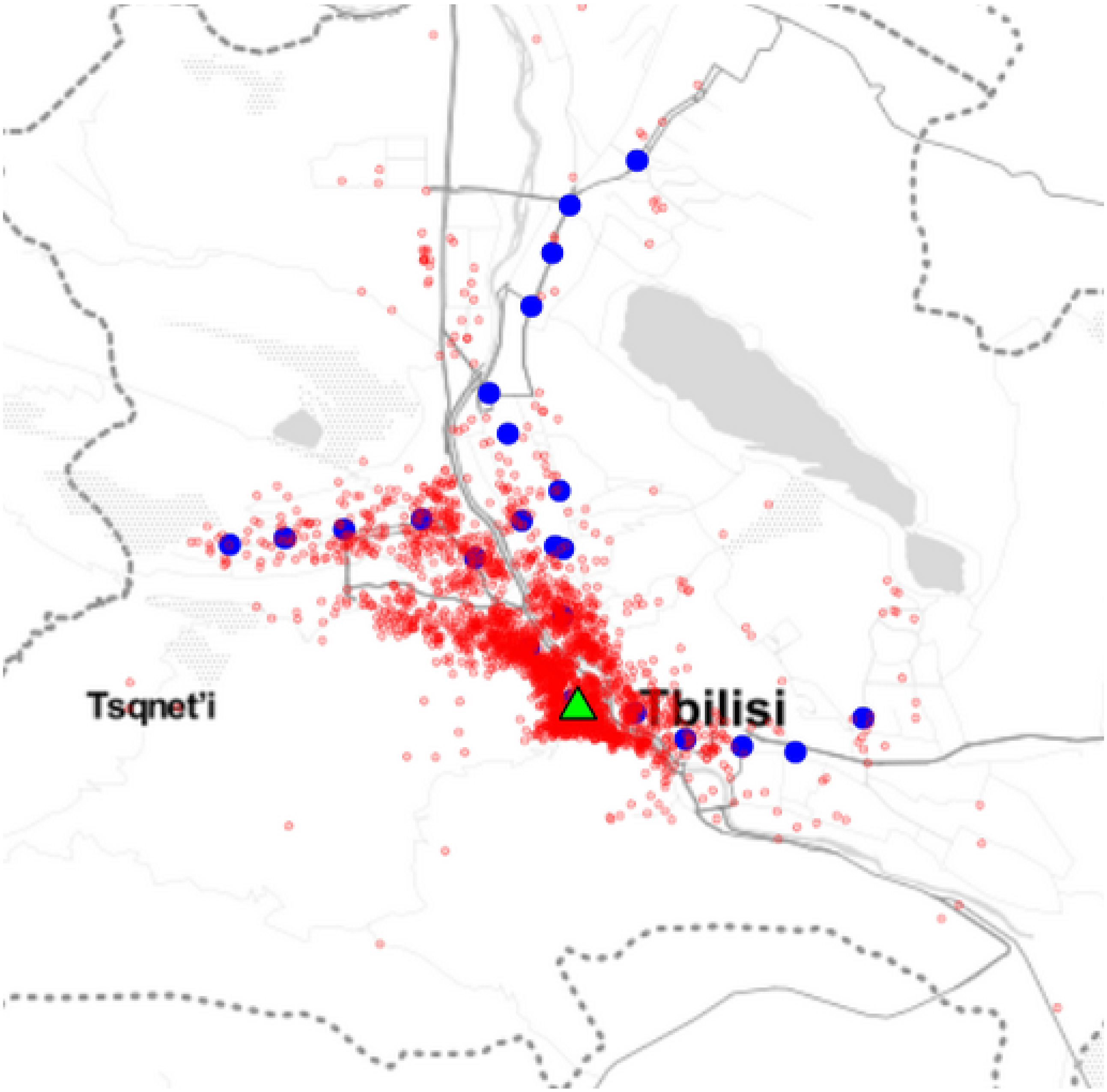

Figure 16: Volgograd: The Square of the Fallen Fighters (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

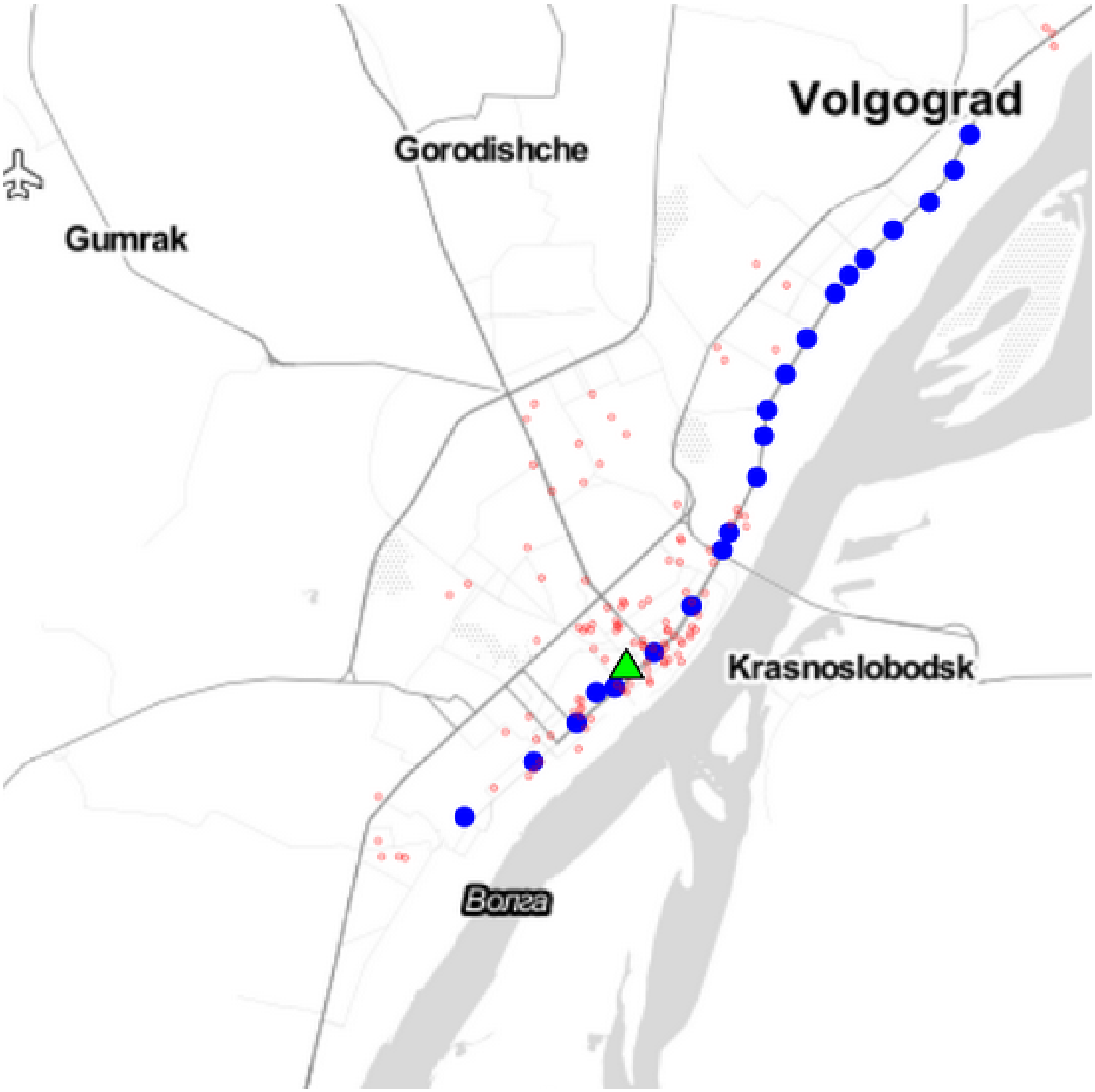

Figure 17: Yekaterinburg: 1905 Year Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

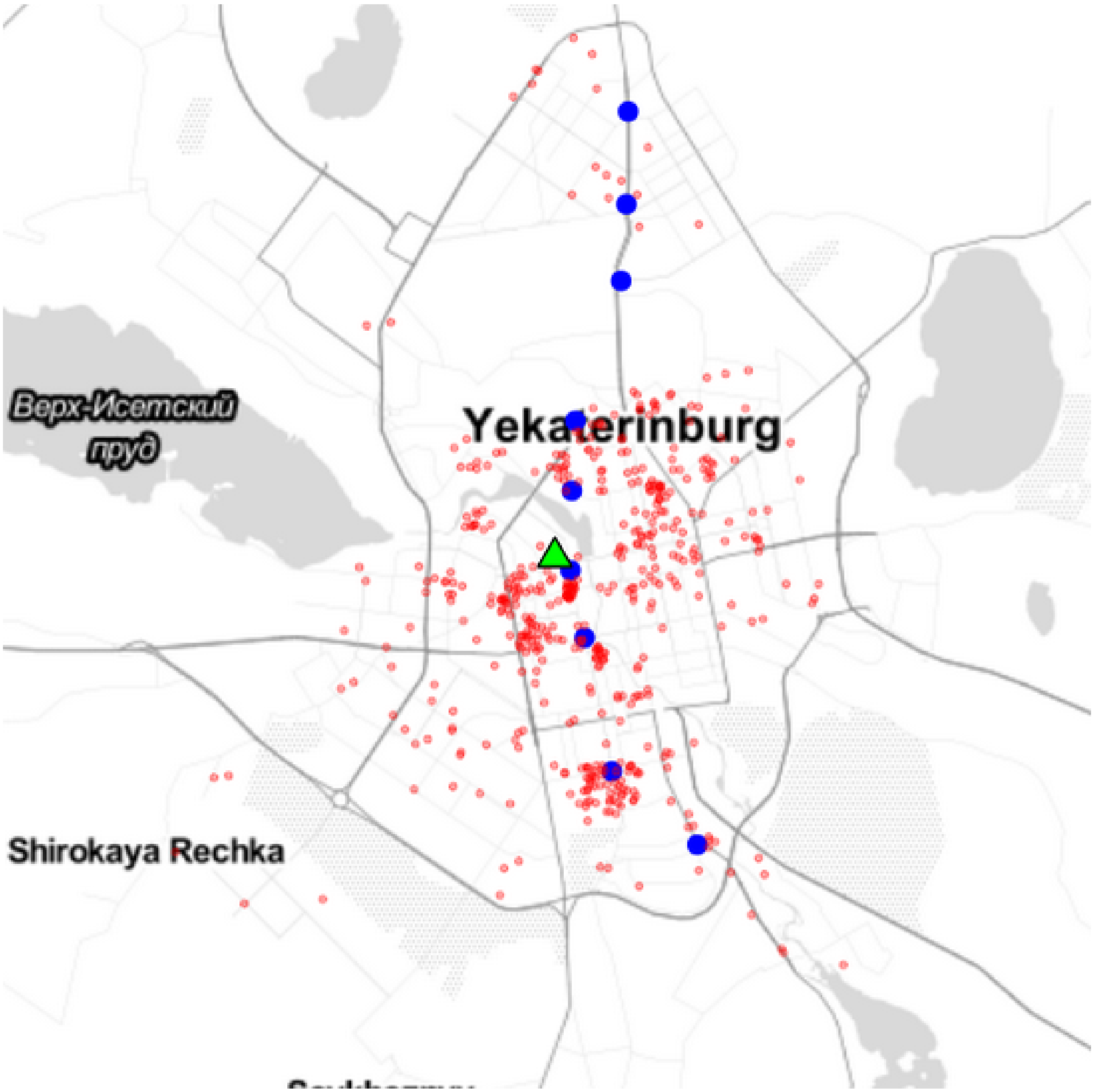

Figure 18: Yerevan: Republic Square (green triangle), subway stations (large blue dots) and Airbnb apartments (red dots)

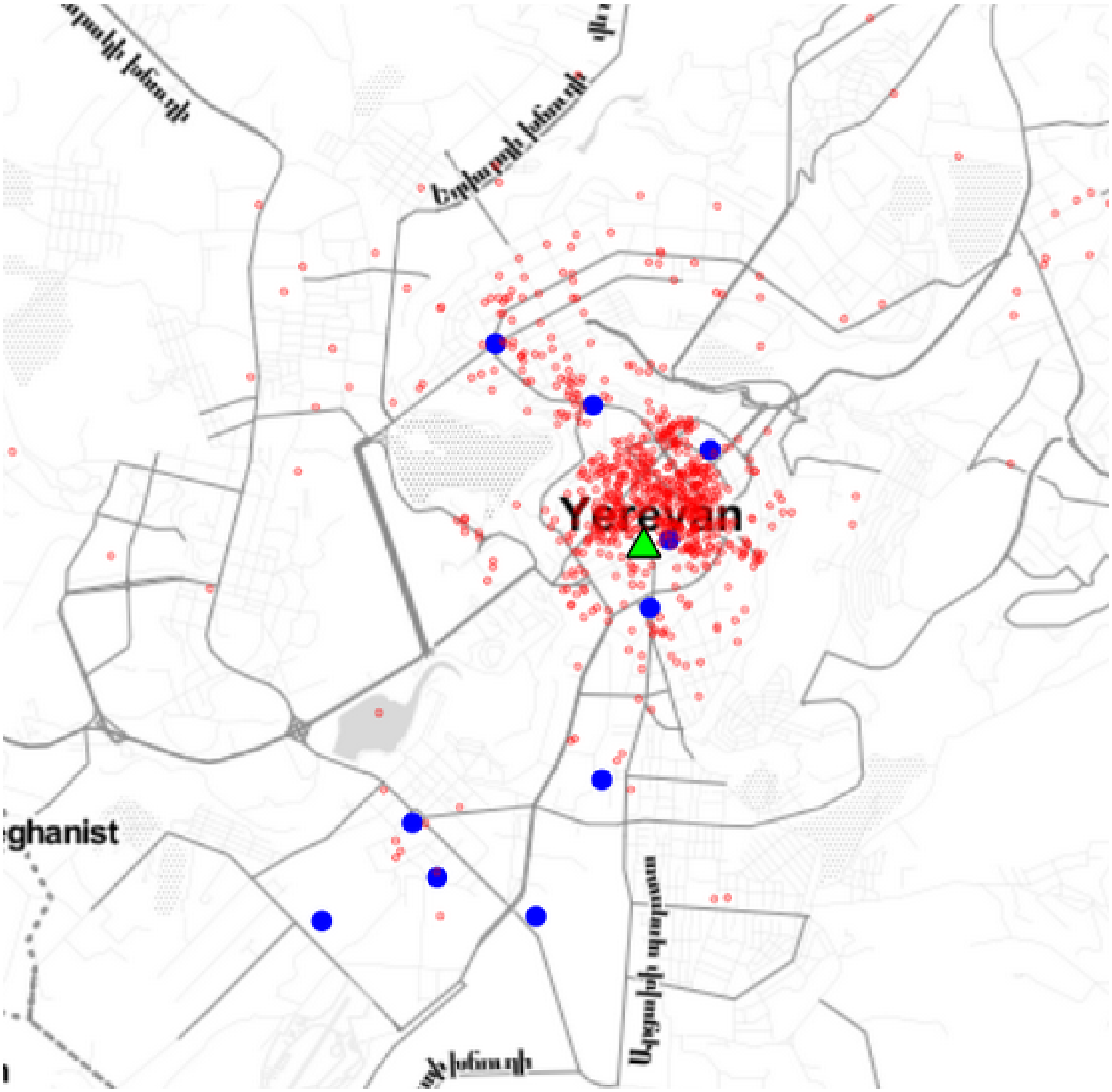

Figure 19: Hierarchial clustering of cities according to subway development level

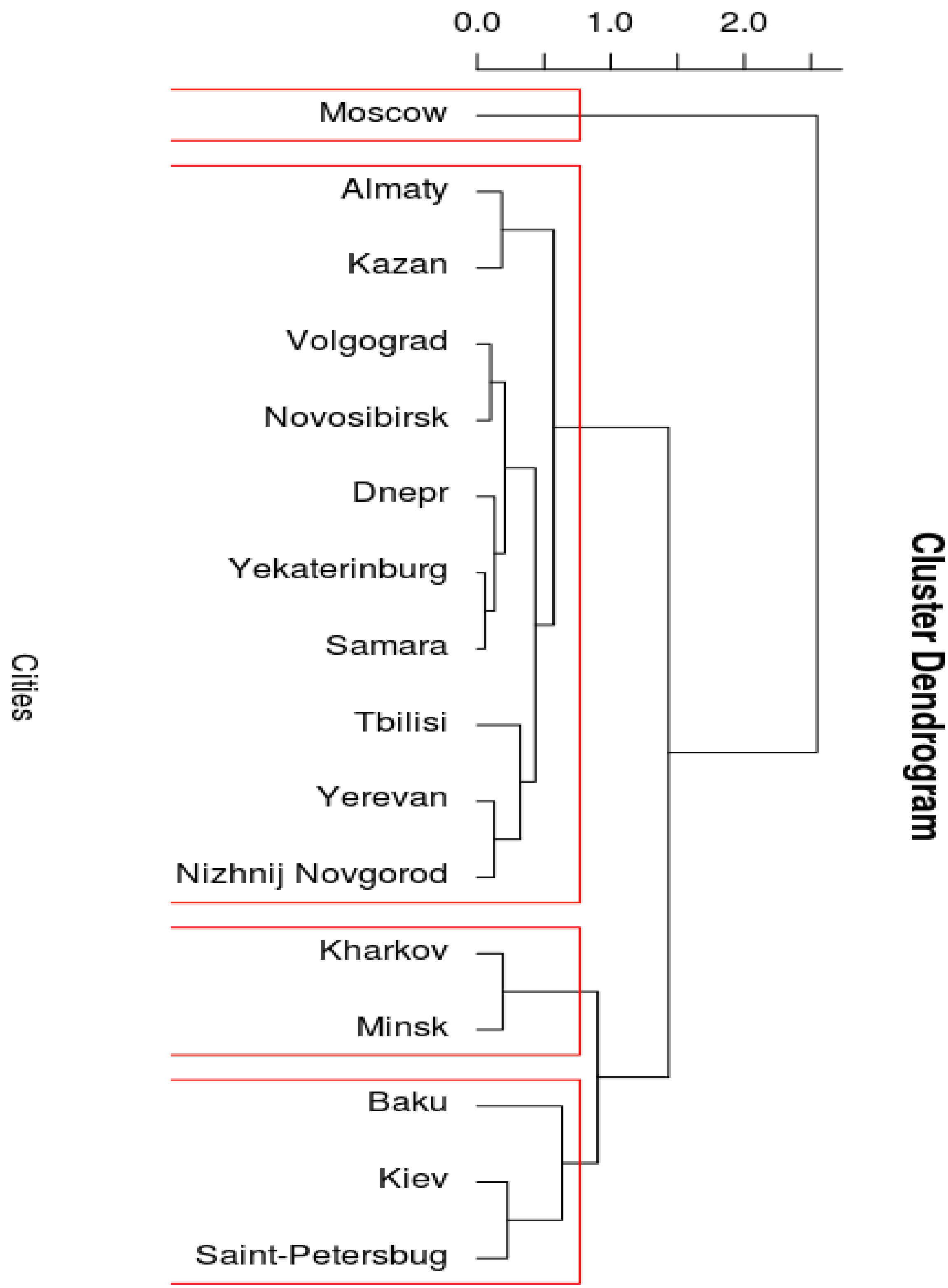

Figure 20: Distance-to-subway coefficients vs. subway system development (triangles and green colour stand for significant coefficients)

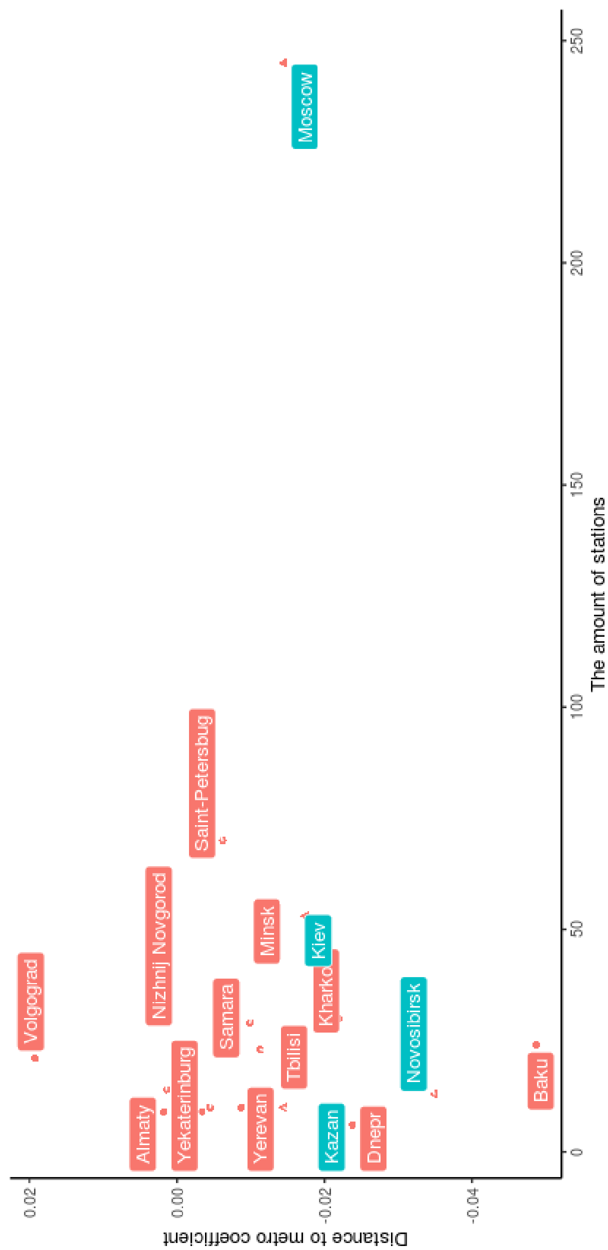

Figure 21: The number of observation for each city