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Spatial Competition and Transport Infrastructure: The Case of Moscow Office Rental Market

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Spatial Competition and Transport Infrastructure: The Case of Moscow Office Rental Market*

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(Preliminary and incomplete)

Abstract

This paper studies the geography of competition on Moscow commercial real estate market. We estimate the elasticity of office rental price to the prices of competing objects as a function of the geographical distance. We found that office real estate market in Moscow, although saturated, is surprisingly local. The evidence of price competition exists primarily at a walking distance, and dies down quickly at a distances beyond one kilometer. However, if competing objects are connected by a subway line, the geographical radius of competition extends to up to three kilometers. Thus, in the case of Moscow real estate transportation infrastructure works to integrate local markets and promote competition, although the magnitude of these effects are modest.

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1 Introduction

Real estate provides the most obvious example of a good which is differentiated in consumer characteristics and, at the same time, strictly tied to the geographical location. Real estate objects are imperfect substitutes in the eyes of the consumer, yet the pattern of substitution can be nontrivial. Intuition suggests, that both “closeness” in consumer characteristics and geographical proximity should make real estate objects better substitutes. We can think of a person buying a house or a firm renting office space as searching for an “ideal” object – i.e. a set of characteristics, including location. Yet when agents actually make decisions, they consider trade-offs of either price versus characteristics, or one characteristic versus the other, choosing an object among potentially suitable (competing) offers. As the result, real estate objects, although unique, enjoy some amount of market power, but it is limited by competition. In this paper we study the geographical structure of this competition in the real estate market, how this geographical structure interacts with differentiation in product characteristic space, and how such features of urban geography as transportation infrastructure can promote competition.

We study the market for rental office space in the city of Moscow. Our main question is how “local” is this market, indeed? How strongly do comparable offices compete and how does this competition depend on the geographical distance. We are also interested in what makes the effective “distance” shorter or longer, and hence competition stronger or weaker. The modern city is not a homogeneous disk a la von Thunen. Transportation infrastructure makes effective distances “shorter”, cutting cost for workers commuting to jobs and firms trying to reach their customers. But transport infrastructure does not reduce costs uniformly, it creates complicated urban geography, where some places are connected better than the others. Our interest is to explore the role of transportation infrastructure in market integration.

This paper contributes to three stands of the existing literature. First, we provide one of the few studies of Moscow commercial real estate markets. Since the breakup of the Soviet Union the real estate markets in Russia had to develop anew. Moscow is without a doubt

a most vibrant of all post-Soviet markets yet scarcely studied to date. Bertaud & Renaud (1997) studied the consequences of the Soviet land use policy for the real estate market and urban geography of socialist cities. Zharov (2011) calculated an analog of a repeat-sales index for commercial real estate in Moscow as well as hedonic index. We extend this strand of literature further studying the features of price behavior in Moscow's commercial real estate.

In the vast hedonic literature (since Griliches (1971), Rosen (1974), and Epple (1987)), a heterogenous good is viewed as a bundle of characteristics, each of which has a well-defined shadow price. Therefore, the price of a house is determined as a linear combination of these shadow prices and characteristics' endowment. When applied to the office markets, the hedonic analysis has shown that among the most important drivers of rental rate formation are such factors as: distance to the nearest subway (recently for commercial real estate: Cervero & Duncan (2002)), distance to the central business district (Clapp (1980)), rentable floor area and building age (Bollinger, Ihlanfeldt & Bowes (1998)), number of stories of a building, story's height (Shilton & Zaccaria (1994)), etc. Moreover, the presence of such spatial amenities as restaurants, shopping and commercial centers, nightclubs, banks, historical landmarks nearby the office are reflected in its rental rates (for example, Mills (1992)). We estimate a hedonic model for Moscow and compare its features to the existing literature on other markets. Overall, it turns out that modern Moscow commercial real estate market is not atypical: same features are found to be the strongest drivers of the price.

Second, this paper uses detailed geographical data to study one of the aspects of cities. With availability of detailed geographically-coded data and the development of econometric methods geography of firm entry, knowledge spillovers, product competition, and many other aspects of economic activity in the geographical space has been studied. Rosenthal & Strange (2003) used detailed geographical data to study the geographical extent of production spillovers. We are looking at the geographical extent of market integration.

Finally, we are able to draw on and providing an application of the techniques to study spatial competition. Real estate has been studied with the use spatial econometric techniques (recently, for example, by Iwata, Sumita & Fujisawa (2012)). Pinkse, Slade & Brett (2002)

offered a methodology to measure cross-price elasticities for a set of goods, differentiated by location. We plan to extend and implement their methodology on the data on Moscow office real estate. We contribute to the literature by introducing transport infrastructure and transport connections explicitly into the measures of market “distance”. The semiparametric methodology is naturally flexible and allows to discriminate between alternative definitions of a “distance”, which allows us to measure the role of transport.

The paper is organized as follows. Section 2 gives a theoretical setup and derives the estimating equation. Section 3 discusses the data. Section 5 presents the preliminary results. Section 6 concludes.

2 Theoretical setup

Consider an environment with N real estate objects (offices). Objects are either occupied by a tenant or may become vacant. Vacant object could be put on the market. To simplify the analysis, we assume that the objects can become vacant exogenously and independently of market conditions. We also assume that the decision when to put the object on the market is non-strategic and just follows whenever an office becomes vacant. To put it differently, we assume that the costs of waiting (potential rent lost) outweighs potential the benefits (chance to time the market).

When object i is put on the market, its owner (agent) sets a rental price p_i , advertises a vacancy, and waits for a potential tenant. Every object is characterized by a vector of observable features X_i such as office class (A, B, B+ etc), location, size of the available office space, building characteristics, available infrastructure, etc. An agent knows the characteristics of his own objects and can observe prices and characteristics of all objects currently on the market. This information is taken into account when an owner selects a price offer p_i .

The matching between buildings on the market and renters is assumed to occur when a potential tenant with a valuation of the object above the level of offered price p_i appears. We assume the Poisson arrival process of potential tenants with the constant arrival rate $\lambda(p_i, X_i, p_m, X_m, \epsilon_i)$, a function of object’s own offered price and characteristics and of the

prices and characteristics of all other objects concurrently on the market (competitors). p_m and X_m are vectors of prices and characteristics of competitors, ϵ_i represents all unobservable factors specific to the object i .

Let a discount factor be r . After a match at time t owner collects rental payments p_i either forever, getting the total discounted sum of future revenues $\int_t^\infty p_i e^{-rs} ds = \frac{p_i}{r} e^{-rt}$, or until the match is dissolved. Assuming that the dissolution of the match happens randomly and exogenously allows to ignore this case without the loss of generality (the expression for discounted future revenues is then the same up to a constant).

The owner's problem is to set a price, maximizing present value of future discounted rental revenues. Since arrival rate λ is lower the higher is the price, an owner faces a trade-off between higher per-period revenues on one hand and shorter time waiting for a tenant on the other hand. An objective function of an owner who sets the price p_i is:

$$\int_0^\infty \lambda_i e^{-\lambda_i t} \frac{p_i}{r} e^{-rt} dt = \frac{\lambda_i p_i}{r(\lambda_i + r)} \quad (1)$$

where $\lambda_i e^{-\lambda_i t}$ – probability density function of the first arrival, $\frac{p_i}{r} e^{-rt}$ – value of discounted payments that owner receives afterwards.

Differentiating (1) with respect to p_i , get the first order condition for an owner's problem:

$$\left[\left(\frac{\partial \lambda_i}{\partial p_i} p_i + \lambda_i \right) (\lambda_i + r) - \frac{\partial \lambda_i}{\partial p_i} \lambda_i p_i \right] \frac{1}{r(\lambda_i + r)^2} = 0. \quad (2)$$

Simplifying (2), get

$$\frac{\partial \lambda_i}{\partial p_i} p_i r + \lambda_i r + \lambda_i^2 = 0. \quad (3)$$

Under an assumption that λ_i is a multiplicative function of object's own price, own characteristics, and price and characteristics of competitors on a relevant market:

$$\lambda_i = \alpha_0 p_i^{\alpha_i} p_m^{\alpha_m} \exp \left(\sum_k \beta_k X_{ik} + \sum_k \gamma_k X_{mk} + \epsilon_i \right), \quad (4)$$

the first order condition is further simplified into:

$$\lambda_i = (\alpha_i + 1)r. \quad (5)$$

Taking logs, plugging (4) in, and collecting all constant terms, get a linear expression for the log-price:

$$\ln(p_i) = Const + \sum_k b_k X_{ik} + a \ln(p_m) + \sum_k \gamma_k X_{mk} + \varepsilon_i. \quad (6)$$

That is, a discounted future rental payments-maximizing price level is a function of the own characteristics of an object, and the prices and characteristics of the competitor objects. We estimate equation (6) in two steps. First, in section 5.1 we estimate a hedonic price model:

$$\ln(p_{it}) = c_t + \sum_k b_k X_{ik} + \nu_{it}, \quad (7)$$

where average for a time period values of the price levels and average characteristics of the objects on the market are absorbed by the time dummies c_t . To simplify, we assume that the local composition of competitor characteristics does not change separately from the market. Under this assumption ν_{it} represents the part of the optimal price that is not explained by the average market conditions and individual office characteristics, but depends on unobservable factors and deviations from the average hedonic price by the immediate competitors who draw from the same pool of potential renters:

$$\nu_{it} = c + a\nu_{mit} + \varepsilon_i \quad (8)$$

In equation (8) ν_{mit} is an aggregate of the residuals of the competitor prices, the part of the price that is not explained by hedonic characteristics of the competitors. How to aggregate the prices ultimately depends on our understanding of a market's extent. In other words, it depends on the degree of substitutability between objects from the point of view of the consumer (potential tenant). Substitutability of objects depends on similarity

of their characteristics. In our examples such characteristics are features of the office and its location. Similar objects that are close by should affect each other optimal price more (i.e. compete stronger) than offices of different class located across the city from each other. To capture this, we model market price aggregate as weighted average of competitor prices, where weights depend flexibly on the similarity between objects. Let p_{mi} denote an aggregate of competitor prices for an object i and assume:

$$\ln(p_m) = \sum_{j \neq i} w_{ij} \ln(p_j), \quad (9)$$

where w_{ij} is a measure of inverse “distance” between object i and object j .

In the second stage of our empirical analysis in section 5.2 we parameterize w_{ij} by the characteristics of relative geographical location between objects and differences in characteristics, to estimate empirically how “close” should the objects be to affect each other market prices. We analyze the behavior of hedonic residuals, $\hat{\nu}_{it}$, the part of the price that is not explained by office quality or macroeconomic factors. Equation (8) becomes:

$$\hat{\nu}_{it} = c + a \sum_{j \neq i} w_{ij} \hat{\nu}_{jt} + \varepsilon_{it} \quad (10)$$

3 Data

3.1 Office rental deals

The empirical estimation relies on the database of Moscow office leasing deals provided by one of the largest real estate agency in Moscow, which contains about 8,300 deals overall. The database was collected by the agency for the purpose of market analysis and it covers all office leasing deals in Moscow in 2001 - 2010 assisted by this agency and all public listings collected by the analytic department of the agency from open sources. For each deal there is the latest available rental rate per squared meter (in US dollars), the date when office was first advertised for rent, the date of the deal, the date when a new tenant moves in.

Each office in the database is assigned a nearest subway station and walking distance to

the station in minutes. For a majority of the offices an exact location is known, down to longitude and latitude of the building. For a subsample of offices location information was restored by us by examining the neighborhood of respective the subway station for a building with given characteristics. Geographical coordinates allow us to calculate the distance to Moscow center (the Kremlin) and straight-line geographical distance between every pair of offices.

We also have information on various physical characteristics of offices available in the data base such as:

- Office space offered for rent (in squared meters);
- Ceiling height (in meters);
- Floor of an office;
- Number of parking slots per object;
- Number of floors in the building;
- Date of construction;
- Office space location in the basement or in the first floor;
- Office renovation category (shell-and-core, fully-renovated, etc);
- Operating expenses(U.S. Dollars per square meter).

In addition there are some characteristics of the deal itself (i.e. possibility of further office space buy-out by a lessee, minimal rent term offered (in month) and the lessee (foreign or domestic company). Table 1 provides descriptive statistics of the main variables used in the analysis.

However, it is important to notice that a more general characteristic of the office is its class, which when assigned takes in account almost all office characteristics mentioned above. Listed in the descendent order of quality, there are four classes of offices accepted by the

Variable	Obs	Mean	Std. Dev.	Min	Max
Net rental rate (US \$ per m^2)	7504	576.6	309.2	90	2740
Exposition time (days)	8352	141.7	209.9	0	2497
Office space (m^2)	8250	884.8	2052.6	30	96000
Operating expenses (US \$ per m^2)	6626	78.3	28.3	10	400
Distance to subway (minutes walk)	8181	10.1	15.8	1	25
Distance to center (km)	8356	26.5	381.6	.18	6856.2
# parking slots	5905	257.5	337.3	0	3600

Table 1: Office characteristics. Descriptive statistics.

real estate agencies of Moscow: A, B+, B- and C. We omit all unclassified offices, which are about 1% of the sample.

Apart from class, each office is matched by its location to the one of the fifteen geographic submarkets according to the well-adopted among Moscow real estate agencies classification. We exclude all the offices located outside Moscow’s Ring Road. Table 2 summarizes the distribution of offices by class and submarket.

Submarket	A	B+	B-	C
Central business district	182	847	326	48
Belorussky	83	385	45	19
Basmanny	31	221	137	75
City	77	28	0	0
Frunzenskaya	39	79	16	21
Kutuzovsky	1	88	13	4
Novoslobodsky	30	340	83	37
Shabolovsky	18	378	156	109
Sokolniki	26	113	58	21
Tagansky	45	123	57	21
Zamoskvorechye	196	290	139	29
North-East	3	162	128	128
North-West	28	107	151	36
South-East	0	128	120	47
South-West	12	277	37	15

Table 2: Distribution of offices by class and geographical submarket

We drop years 2001-2003 from the sample, because generally, the number of observed transactions in the sample is smaller in those years, and there might not be sufficient observations on offices on the market in the same geographical vicinity concurrently. We focus on

2004-2009 period, where there sample becomes much wider. We also drop all observations with missing data on either rental price, opening date, or date of the deal. We drop cases with overly long market exposition (more than 300 days). Finally, there are observations with obvious mistakes (outliers by an order of magnitude) in price. This leaves us with a cleaned sample of 4307 observations.

The set of characteristics of objects and characteristics of rental deals was used to estimate a hedonic model of price and to build a hedonic price index in section 5.1.

3.2 Transportation infrastructure

We complement the data on location of offices with the information about transport connections. At this stage, we use the structure of Moscow subway system.

Moscow subway has 11 underground lines and two short above-the-ground lines (for an illustration see the current official map, Figure 11 in the appendix). The lines are color-coded and numbered. The Moscow subway system has circle-radial structure. Underground system consists of one circle line in the center of the city, 9 major radial lines, and Kakhovskaya line of 3 stations. The commuting patterns are typical of a monocentric city: residents live on the outskirts and commute to the center for work. Thus, from the point of view of office personnel, transport accessibility is the best for offices in the center or on the same radial line as their residence. Thus, we focus on radial lines when describing relative transportation opportunities between two office locations: two offices on the same radial line are “closer” to each other than two offices on the different radial lines, *ceteris paribus*.

All the offices in the database are coded to the nearest underground subway station. We assign offices to radial lines. If an office is located near the one of the stations in the transfer node (where passengers can change lines), we code this office as being accessible from all of the lines that go through the transfer node. For every pair of offices we can then use a binary measure of being on the same subway line to complement our measure of straight-line geographical distance. In section 5.2 we use these measures to look at the price reactions between offices that are located on the same subway line, versus price reactions between offices on the different subway lines.

4 Specification details and estimation issues

We estimate equation (10) with different specifications of w_{ij} in order to explore the extent of the relevant market in the geographical space and in product characteristic space. We consider the following specifications:

- Concentric circles. We assume that office objects compete by reacting to the average price (hedonic residual) of the competitors concurrently on the market and inside a certain geographical radius. We define concentric zones around each object on the market and estimate the price reaction to the average hedonic residuals in the different zones (for example: average in 1 kilometer radius, average of objects between 1 and 2 kilometers, and so on). Equation 10 becomes:

$$\hat{\nu}_{it} = c + \sum_l a_l \sum_{j \neq i} \frac{1}{n_{il}} \hat{\nu}_{jt} + \varepsilon_{it}, \quad (11)$$

where n_{il} - number of office i 's competitors in the concentric zone l .

- Nearest neighbor. We assume that office objects compete by reacting to the geographically closest object concurrently on the market. We also assume that the strength of price reaction is a function of distance, and approximate this function with a fourth-degree polynomial. Equation (10) becomes:

$$\hat{\nu}_{it} = c + \sum_{l=0}^4 w_l d_{ij}^l \hat{\nu}_{jt} + \varepsilon_{it}, \quad (12)$$

- Competition inside the narrow product space subclass. We also estimate the above specifications, assuming that competition is strong enough only among objects that are close in consumer characteristics. That is, we only consider offices concurrently on the market competitors if they are of the same class and size.
- Considering the role of transport infrastructure. Modify equations (11) and (12) to allow for different price reactions between offices connected by transport infrastructure, and offices without such connections. Here we test whether urban transport links make

competition stronger over the same geographical distances, i.e. whether transport helps "shrink" the geographical space and promote integration of local markets.

Another issue to consider is possible endogeneity. If some unobserved factor affects real estate prices locally, and if this factor is common to all the objects in the geographical vicinity, then positive correlation of hedonic residuals of neighbouring objects may be observed even if objects set their prices independently, even if objects do not compete at all. Thus, endogeneity tends to bias upward the estimates of price reaction and, as the result, we would overestimate the extent of competition. One needs to use instruments for the neighbour price shock to solve the problem of endogeneity.

Consumer characteristics of neighbour objects often used as instruments in spatial competition settings. The difficulty in the case of Moscow real estate is that consumer characteristics of offices are, in turn, spatially correlated. Expensive offices are located in the city center, in prestigious districts. Modest offices are often located in the outskirts. Among the office characteristics we observe, suitable instruments are characteristics related to the transaction (foreign tenant, length of contract) and characteristics that do not have a clear relation to the neighbourhood (size of office, floor). Unfortunately, these instruments are rather weak.

Another set of instruments might come from lagged values of prices or characteristics of offices from the same neighbourhood. We use different sets of instruments and report the results in the next section.

5 Results

5.1 Hedonic price model

We estimate a hedonic model (equation (7) for a logarithm of rental price for rental deals from January 2004 to March 2010 with quarter dummy variables. Results are presented in Table 3. Dummy for class C and dummy for buildings newer than year 2001 are omitted to avoid multicollinearity.

Empirically, distances to the nearest subway and to the center of the city are two strongest

factors that affect price. Age of the building or availability of parking have no statistical effect on the rental rate. There is a moderate discount for basement and attic office space. First floor is indistinguishable from the rest of the building. Offices in separate buildings rented out in entirety demand a premium over comparable properties. There is no visible discount or surcharge for small and large office spaces (this is robust to alternative small/large thresholds). Tenants prefer offices ready to move into, as “shell&core” condition commands a small discount. Foreign companies appear to pay more *ceteris paribus*, but the effect is relatively minor. Option to buy increases rental price, delay to move in does not affect the price significantly.

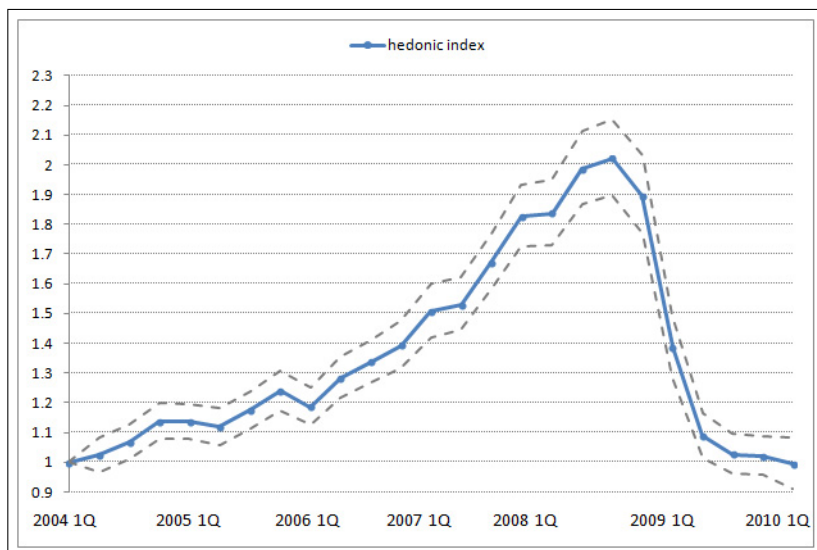
The most important observable characteristic of the office is the class, which could be thought of as a composite measure of quality. Indeed, characteristics that office has to have in order to be classified as class “A” include availability of parking and other features of necessary infrastructure. In a sense, many of the explanatory variables in the hedonic model are redundant once class is accounted for.

The quarter dummy variables estimated in the hedonic model provide a time series of “average” office rental price cleaned out of the composition of individual characteristics of the objects on the market. In other words, it is a hedonic time-series index of office rental rates. Picture 1 plots an index over 2004-2010.

Moscow commercial real estate went through a period of boom from the early of 2000s to the beginning of global financial crisis at the end of 2008. By the beginning of 2010, a sharp drop brought prices down to the levels not seen since 2004. Actual average rental prices in 2010 were slightly higher than 2004 level, but hedonic index is below 2004 level, which is explained by the constantly improving quality of office space pool in Moscow.

5.2 Spatial competition

We now turn to the analysis of the hedonic residuals $\hat{\nu}_{it}$, estimating equation (10) for different specifications of w_{ij} . Strength of competition between offices that are concurrently on the market (opening ad date prior to, and closing date after the date of the deal with object i) and object i is assumed to depend on the geographical distance. First, we consider a



Dashed lines represent 95% confidence interval

Figure 1: Hedonic index of office rental rate in Moscow, 2004-2010.

specification with concentric ring zones of neighbor competing offices, then a specification where office competes with the nearest neighbour. For both approaches we try expanding or narrowing the space of competition in product space characteristics

5.2.1 Specification with concentric zones

In this subsection we discuss the details and the results of estimation for the equation (11).

First, we split all competing objects in Moscow into four concentric zones: objects that are within 1 kilometer of office i , objects that are between one and two kilometers away, between 2 and 5 kilometers, and objects farther than 5 kilometers. The choice of zones is restricted by data availability: for example, for many objects it is not easy to find a competing object closer than one kilometer at any given time. One kilometer is a compromise that allows us to keep reasonably large number of observations.¹ On the other hand, one kilometer or 15 minutes on foot is commonly considered a typically reasonable walking distance in Moscow, and we should expect to see an integrated market at such a distance. For each ring zone, we calculate a simple average hedonic residual $\hat{\nu}_{it}$.

Second, we divide offices into class groups to capture the fact that substitutability requires

¹Qualitatively, our results are robust to the choice of distance thresholds. On the other hand, the wider are the ring zones, the fewer offices end up with no “neighbors” and fewer observations lost.

closeness not only in geographical space, but also in the space of product characteristics. We assume that class “A” and class “B+” offices belong to the same subgroup, compete with each other, but do not compete with class “B-” or “C” offices. Same way, “B-” and “C” class are combined into a subgroup and assumed to compete only among themselves.² Within each class group we assume that the strength of competition depends on distance.

Third, we introduce the topography of Moscow subway into our distance measures. Offices within one kilometer are aggregated as before. For all other distance zones we aggregate prices of competing offices separately for the offices located on the same radial subway line and on the different subway lines.

Equation (11) first estimated via OLS. The results are presented in Table 4 in appendix.

Column (1) presents the results for the case when offices are assumed to compete globally in product quality space, i.e. each office competes with all neighbours regardless of their quality class. The correlation between price residuals gets weaker with the distance and is not different from zero statistically at 2 kilometers and beyond. Negative correlation at the distances of above 5 kilometers can be explained by spatial fluctuations in consumer demand: when one of the geographical submarkets experiences excess demand, in relative terms, the rest of Moscow loses renters.

Measured correlation is very weak even for the offices in the immediate vicinity: only 16% of the price shock is translated to the neighbours. Either the competition among offices is truly weak, or we should consider more narrow subgroups by consumer characteristics. Column (2) and column (3) repeat the exercise for the offices of the same class and for the offices of different class.

Column (2) shows that the price response grows to about 20% for the immediate vicinity. In contrast, column (3) does not show a logical competition pattern, which is what expected for the offices that are poor substitutes for each other.

Columns (4) and (5) present the results for offices of the same class, connected or not connected by the subway line. For offices on the same subway line the price correlation is slightly stronger and remains statistically significant over larger distance.

²This structure of competition was suggested in a private interview by a real estate analytic.

Price correlations as functions of distance are plotted on figures 2 - 4.

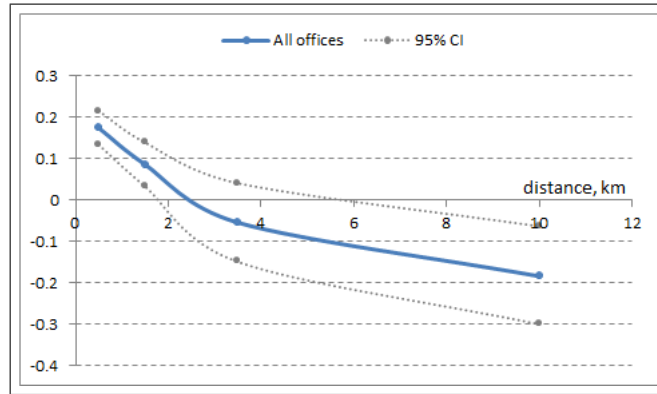


Figure 2: Price response function, all offices. OLS estimation.

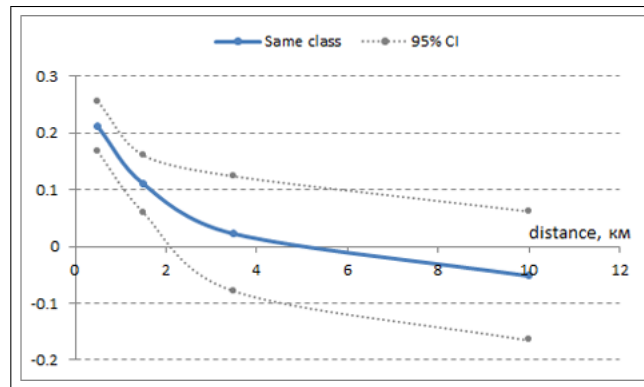


Figure 3: Price response function, offices of the same class. OLS estimation.

Next step is estimating the same relationship using instrumental variables. We use average hedonic residual for office transactions in the past three months in the same geographical area as instruments. Since endogeneity of local unexplained shocks only applies to the immediate geographical vicinity (shocks, common to the larger geographical submarket areas are picked up by submarket dummies in the hedonic model), we instrument only the average price shocks inside one or two kilometer radius. Estimation method is 2-stage least squares. The results are presented in table 5.

The most surprising result is that the price response in the immediate vicinity jumps to 60% of the neighbour price shock. Most likely, this is because of the correlation between prices inside one kilometer radius and prices in one to two kilometers ring. Hedonic residual of 1 to 2 km ring has explanatory power in the first stage regression.

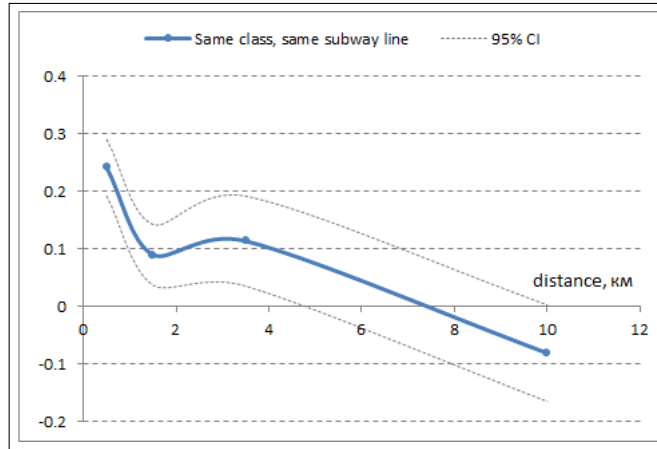


Figure 4: Price response function, offices of the same class, same subway line. OLS estimation.

When we restrict competition only to the offices on the same subway line, the results do not change dramatically. Table 6 presents the estimation results.

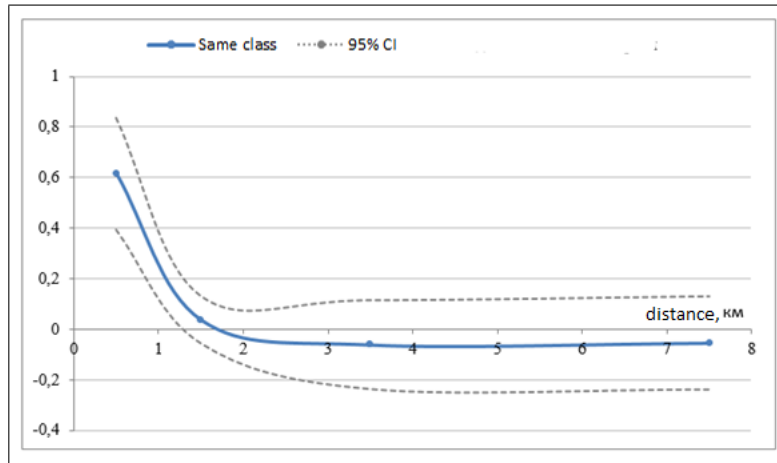


Figure 5: Price response function, offices of the same class. 2SLS estimation, endogeneity in 1 km radius.

Statistically, the response function with and without subway connection are indistinguishable. The results are rather counter-intuitive. The culprit might be in the quality and validity of the instruments. If local shocks are persistent, so that the 3-month lagged values of hedonic residuals cannot be considered exogenous, the 2-stage least squares results are biased. Considering alternative instruments are thus the logical line of future research.

We now turn to the specification, where competition is between two nearest neighbours.

5.2.2 Competing with the nearest neighbor

Equation (12) is estimated first via OLS and then using IV. OLS estimation results are presented in table 7.

Figures 6- 8 illustrate the resulting price response function of distance.

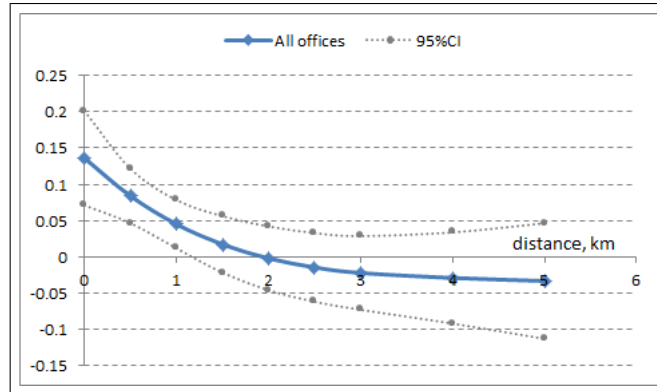


Figure 6: Price response function, nearest office of any class. OLS results.

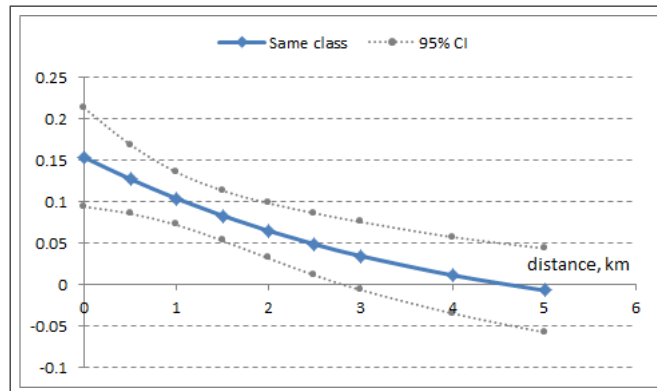


Figure 7: Price response function, nearest office of the same class. OLS results.

Column (1) and figure 6 presents a model that does not distinguish office class. The price response function quickly dies down, becoming indistinguishable from zero at the distance of about 1.2 kilometers. Reaction to the nearest competitor of the same class stays strictly positive until approximately 2.8 kilometers. Finally, offices of the same class and on the same subways line compete at the distances of up to 3.2 km. The strength of competition is modest, though. Only about 15% of the shock is translated into the neighbour price even in the immediate geographical vicinity.

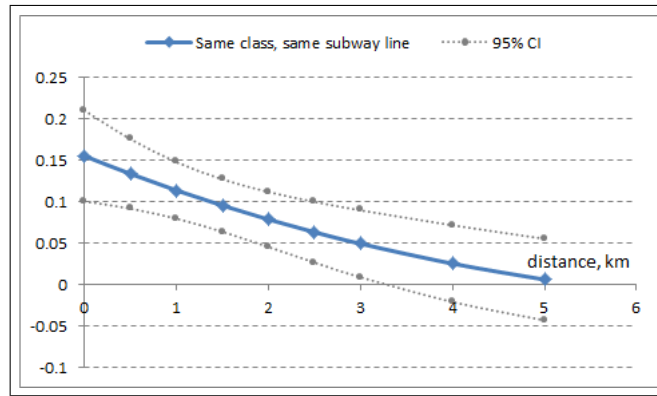


Figure 8: Price response function, nearest office of the same class, same subway line. OLS results.

These results, however, suffer from the same critique of ignored endogeneity. As a next step, we use three-months lagged prices of the nearest neighbour as instruments and estimate equation (12) by GMM. The results are presented in table 8.

The confidence bounds of the response function are understandably wider with the use of instrumental variables, which makes statistical testing for the difference in response to all offices versus offices on the same subway line difficult. However, the difference in magnitude between response functions is visible. Offices on the same subway line give stronger price response, and it remains statistically significant at a larger distance. Figures 9 and 10 illustrate.

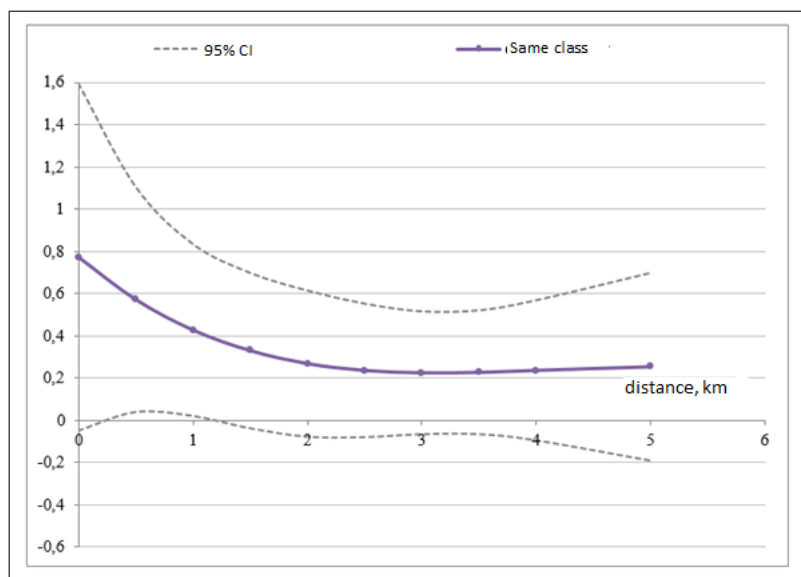


Figure 9: Price response function, nearest office of the same class. GMM results.

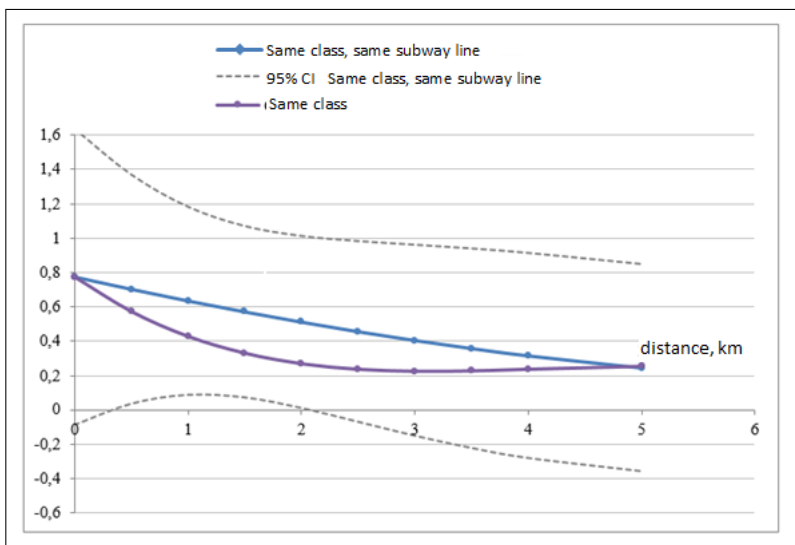


Figure 10: Price response function, nearest office of the same class, same subway line. GMM results . Price response function for all offices of the same class added for comparison.

6 Conclusion

Real estate markets are local. Moscow office rental market is no exception. We found that evidence of strong competition exist only inside a narrow geographical area, practically among the objects at a walking distance from each other. Competition quickly weakens at a distances beyond two kilometers.

Transport infrastructure, as measured by the presence of a direct subway line, extends the geographical boundaries of the market and increases market integration, but the effect is relatively modest in magnitude and in geographical extent. We find limited evidence of competition at the distances farther than three kilometers.

One obvious direction our analysis can be improved and extended is by looking at a wider set of instruments. Using lagged price levels requires assuming strict exogeneity of past price shocks, which might not be realistic in our setting. Using alternative instruments, specifically, a spatial lag of a subset of consumer characteristics would be our next step.

References

Bertaud, A. & Renaud, B. (1997), ‘Socialist cities without land markets’, *Journal of urban Economics* **41**(1), 137–151.

- Bollinger, C. R., Ihlanfeldt, K. R. & Bowes, D. R. (1998), ‘Spatial variation in office rents within the atlanta region’, *Urban Studies* **35**(7), 1097–1118.
- Cervero, R. & Duncan, M. (2002), ‘Transit’s value-added effects: light and commuter rail services and commercial land values’, *Transportation Research Record: Journal of the Transportation Research Board* **1805**(1), 8–15.
- Clapp, J. M. (1980), ‘The intrametropolitan location of office activities*’, *Journal of Regional Science* **20**(3), 387–399.
- Epple, D. (1987), ‘Hedonic prices and implicit markets: estimating demand and supply functions for differentiated products’, *The Journal of Political Economy* pp. 59–80.
- Griliches, Z. (1971), ‘Price indexes and quality change’.
- Iwata, S., Sumita, K. & Fujisawa, M. (2012), ‘Price competition in the spatial real estate market: Allies or rivals?’.
- Mills, E. S. (1992), ‘Office rent determinants in the chicago area’, *Real Estate Economics* **20**(2), 273–287.
- Pinkse, J., Slade, M. E. & Brett, C. (2002), ‘Spatial price competition: a semiparametric approach’, *Econometrica* **70**(3), 1111–1153.
- Rosen, S. (1974), ‘Hedonic prices and implicit markets: product differentiation in pure competition’, *The journal of political economy* pp. 34–55.
- Rosenthal, S. S. & Strange, W. C. (2003), ‘Geography, industrial organization, and agglomeration’, *review of Economics and Statistics* **85**(2), 377–393.
- Shilton, L. & Zaccaria, A. (1994), ‘The avenue effect, landmark externalities, and cubic transformation: Manhattan office valuation’, *The Journal of Real Estate Finance and Economics* **8**(2), 151–165.
- Zharov, I. (2011), *Commercial Real Estate of Moscow Exchange Tradable Index: Hedonic Regression versus Repeat Sales Method*, New Economic School, Master in Finance project, Moscow, Russia.

A Additional figures and tables



Figure 11: Moscow subway system

Dependent variable is ln(gross rental price)	
Explanatory variables	(1)
ln(Walking time to nearest subway)	-0.076 (0.006)**
ln(Distance to center, km)	-0.128 (0.012)**
Class A	0.472 (0.019)**
Class B+	0.298 (0.014)**
Class B-	0.110 (0.015)**
Built earlier than 1990	-0.005 (0.029)
Built from 1991 to 2000	0.010 (0.011)
Parking places per sq meter of office space	-0.087 (0.142)
Entire building for lease	0.062 (0.028)*
Office in the basement or attic	-0.114 (0.028)**
Office on the 1st floor	-0.002 (0.011)
Condition: shell&core	0.025 (0.017)
Condition: fitted out	0.147 (0.020)**
Condition: as is	0.171 (0.024)**
Large space (more than 1000 sq m for lease)	-0.013 (0.020)
Small space (less than 100 sq m for lease)	-0.013 (0.015)
Foreign company tenant	0.035 (0.017)*
ln(Time to wait to move in, days+1)	0.001 (0.005)
Option to buy	0.059 (0.016)**
Geographical submarket dummies	yes
Time dummies	quarter
Observations	4307
R-squared	0.71

Standard errors in parentheses

* significant at 5%; ** significant at 1%

Table 3: Hedonic price model. Results.

Dependent variable is a hedonic price residual

Explanatory variables:	Competing offices				
	(1)	(2)	(3)	(4)	(5)
average hedonic residual	All offices	Same class	Different class	Same class, same metro line	Same class, different mentro line
< 1 km	0.159 (0.022)**	0.206 (0.023)**	-0.022 (0.028)	0.245 (0.025)**	0.190 (0.031)**
1 to 2 km	0.097 (0.028)**	0.116 (0.027)**	-0.141 (0.034)**	0.085 (0.026)**	0.112 (0.029)**
2 to 5 km	-0.095 (0.053)	0.018 (0.055)	-0.303 (0.063)**	0.097 (0.040)*	0.089 (0.069)
> 5 km	-0.188 (0.071)**	-0.050 (0.063)	-0.028 (0.071)	-0.074 (0.041)	-0.012 (0.068)
Observations	3182	2309	1451	1925	1441
R ²	0.02	0.05	0.03	0.06	0.04

Heteroskedasticity-consistent standard errors in parentheses

* 95% significant; ** 99% significant

Table 4: Spatial competition in concentric circles. OLS Results.

Dependent variable is a hedonic price residual

	Endogenous up to 1 km		Endogenous up to 2 km		
	(1)	(2)	(3)	(4)	(5)
	1st stage	2d stage	1st stage		2d stage
	Dependent variable				
Explanatory variables	Average hedonic residual to 1km	Hedonic residual	Average hedonic residual to 1 km	Average hedonic residual 1 to 2 km	Hedonic residual
< 1km		0.614 (0.113)**			0.703 (0.241)**
1 to 2 km	0.146 (0.029)**	0.036 (0.047)			-0.090 (0.302)
2 to 5 km	0.173 (0.062)**	-0.062 (0.089)	0.151 (0.056)**	0.147 (0.043)**	-0.060 (0.091)
> 5 km	0.140 (0.061)*	-0.055 (0.093)	0.154 (0.058)**	-0.006 (0.043)	-0.066 (0.099)
Instruments:					
< 1 km (t-1)	0.299 (0.026)**		0.321 (0.024)**	0.141 (0.018)**	
1 to 2 km (t-1)	0.050 (0.026)		0.078 (0.025)**	0.169 (0.020)**	
Observations	1511	1415	1599	1906	1415
R ²	0.15		0.14	0.09	
F-test on instruments (p-value)	73.95 (0.000)		106.04 (0.000)	74.49 (0.000)	

Heteroskedasticity-consistent standard errors in parentheses

* 95% significant; ** 99% significant

Table 5: Spatial competition in concentric circles among offices of the same class. 2SLS results.

Dependent variable is a hedonic price residual

	Endogenous up to 1 km		Endogenous up to 2 km		
	(1)	(2)	(3)	(4)	(5)
	1st stage	2d stage	1st stage	2d stage	
	Dependent variable				
Explanatory variables	Average hedonic residual to 1km	Hedonic residual	Average hedonic residual to 1 km	Average hedonic residual 1 to 2 km	Hedonic residual
< 1 km		0.568 (0.113)**			0.806 (0.470)
1 to 2 km	0.077 (0.030)**	0.010 (0.040)			-0.377 (0.740)
2 to 5 km	0.025 (0.044)	0.014 (0.056)	0.021 (0.041)	0.113 (0.032)**	0.078 (0.138)
> 5 km	0.083 (0.044)	-0.072 (0.056)	0.048 (0.043)	-0.150 (0.033)**	-0.132 (0.131)
Instruments:					
< 1 km (t-1)	0.316 (0.030)**		0.345 (0.027)**	0.162 (0.020)**	
1 to 2 km (t-1)	0.059 (0.029)*		0.061 (0.028)*	0.085 (0.022)**	
Observations	1161	1111	1268	1467	1111
R2	0.13		0.13	0.07	
F-test on instruments (p-value)	63.10 (0.000)		87.71 (0.000)	43.34 (0.000)	

Heteroskedasticity-consistent standard errors in parentheses

* 95% significant; ** 99% significant

Table 6: Spatial competition in concentric circles among offices of the same class on the same subway line. 2SLS results.

Explanatory variables	Dependent variable is a hedonic price residual		
	(1)	(2)	(3)
	Competing offices		
Distance polynomial	All offices	Same class	Same class, same metro line
w_0	-0.000 (0.003)	-0.001 (0.003)	-0.003 (0.003)
w_1	0.075 (0.024)**	0.090 (0.021)**	0.058 (0.016)**
w_2	-0.029 (0.012)*	-0.029 (0.009)**	-0.013 (0.005)**
w_3	0.003 (0.002)	0.003 (0.001)*	0.001 (0.000)*
w_4	-0.000 (0.000)	-0.000 (0.000)*	-0.000 (0.000)
Observations	4943	4943	4943
R ²	0.00	0.01	0.01

Heteroskedasticity-consistent standard errors in parentheses
* 95% significant; ** 99% significant

Table 7: Spatial competition with the nearest neighbour. OLS results.

Explanatory	Dependent variable is a hedonic price residual	
	(1)	(2)
	Competing offices	
Distance polynomial	Same class	Same class, same metro line
w_0	0.773 (0.420)	0.776 (0.441)
w_1	-0.465 (0.466)	-0.147 (0.300)
w_2	0.133 (0.166)	0.007 (0.053)
w_3	-0.014 (0.019)	0.000 (0.003)
w_4	0.000 (0.001)	-0.000 (0.000)
Observations	4943	4721

Heteroskedasticity-consistent standard errors in parentheses
* 95% significant; ** 99% significant

Table 8: Spatial competition with the nearest neighbour. GMM results.