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Abstract

This paper is the first to document empirically that urban shopping areas have a pronounced centre where the rents are the highest, and a negative rent gradient. We use this insight to build and test empirically a simple theoretical model of the competition between the residential and the retail land in a city. The model predicts that rents and occupancy rates on the edges of shopping areas are most sensitive to changes in economic conditions. Demand shocks may lead to transformations between retail and residential land use, mostly at the edge, and to a contraction or expansion of shopping areas. The model predictions are tested on unique data on the location and characteristics of all retail and non-retail properties within 300 largest shopping areas in the Netherlands in 2004-2014, a period including the Great Recession. With every 100 metre distance from the centre of a shopping area rents fall, on average, by 15 percent. Shopping streets, areas located on attractive sites and areas offering free parking have a flatter distance decay. The vacancy rate on the edge of a shopping area is almost twice as high as in the centre. During the Great Recession some 2% of the retail properties were transformed into other use, mostly on the edges of the shopping areas.

JEL Codes: L81, R13, R3, R4

Keywords: land use, competition, retailers, rent gradient, vacancy, transformation

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1 Introduction

Traditionally, urban economics has focused on the land market for housing and - more recently - business premises (see for a recent application Ahlfeldt et al., 2016 and the references therin). Next to living and working, an important part of the urban space is occupied by retail.[1] Yet, to the best of our knowledge, there are no empirical studies of retail land use. This paper exploits four unique datasets to study the land use in urban shopping areas[2] and the competition between residential and retail land in a city.

Our first contribution is to document that the spatial structure of an average shopping area resembles that of a monocentric city. This holds for shopping areas in downtowns as well as for shopping streets and districts. They all tend to have one pronounced centre where the number of visitors (footfall) is the highest and the rental levels are the highest. The footfall and the rents decrease monotonically with the distance from this centre. Our second contribution is to derive and test empirically a number of implications of the distance decay in rents for the competition between the residential and the retail land use in a city. We show theoretically that: (i) this competition determines endogenously the size of the shopping area; (ii) it helps the shopping areas to adjust to demand shocks such as e.g. brought about by the Great Recession and the rise of web shopping. We provide empirical evidence using rich data on the location and characteristics of all retail and non-retail properties within 300 largest shopping areas in the Netherlands and a sample of retail rent transactions in 2004-2014, a period including the Great Recession.

In our model, shopping areas are located in a city. Their location is exogenously given and they are surrounded by residential land. Competitive retailers (shops) populate shopping areas; they pay rent to absentee landlords for the land they use. Consumers travel to the centre of a shopping area and randomly walk from there to shops located around. Profitability of a shop depends on the number of consumers who visit it, so profits and rents are the highest in the centre of a shopping area and decline with distance from it. Land rents clear the market at each retail location.

Consumers decide to which shopping area to go and how long to stay there, depending

[1] In Dutch urban municipalities 60% of the urban land is occupied by housing, 30% by businesses and 10% by retail and culture.

[2] Our term 'shopping area' refers to various retail concentrations including: a downtown, a shopping street or district, a mall, etc.

on the attractiveness of the place. Conditional on having arrived, the probability that a consumer visits a shop at a certain distance from the centre will be larger the longer the consumer stays in the shopping area. Areas that induce consumers to stay longer, for instance due to the presence of attractions such as historical monuments or due to zero parking costs, will thus have a flatter land gradient. Areas with a one-dimensional geometry (shopping streets) will also exhibit a flatter land gradient.

Retail land use competes with alternative, often residential, land use. In the center of a shopping area retail bid-rent is higher than the residential bid-rent and land is optimally allocated to retail. If the size of a shopping area is determined endogenously, then the area will expand until, on the boundary, the retail land rent equals the residential land rent. This no-arbitrage condition ensures that land is attributed to the use with the highest bid-rent. Closer to the edge of a shopping area one can thus expect to see a mix of retail and non-retail properties.

A negative shock in demand for retail products, such as that seen during the Great Recession, results in a downward shift of the retail bid-rent curve. In our model, this should lead, in the long run, to a contraction of the shopping area due to the transformation of retail properties on the edge into residential use. In the short run, however, the size of the shopping area is likely to be given. Then a negative demand shock may lead to a negative bid-rent on the boundary, resulting in vacancy there. Hence, vacancies should cluster on the edge. Furthermore, a negative shock in demand should lead to (i) a simultaneous rise in vacancies and fall in rents; (ii) transformation of land from retail to other use, more so on the edge.

We apply this theoretical framework to a selection of some 300 of the largest shopping areas in the Netherlands comprising 40% of the country's total retail, and show that our monocentric land use model provides a good description of their spatial structure. We determine the centre of each shopping area empirically as the spot with the highest density of shops. We also test the robustness of our results against other possible definitions of the centre. We show that shopping areas tend to have a pronounced centre and a strong and robust distance effect in all our variables of interest. On average, rents decrease by some 15% with every additional 100 metre distance from the centre. In shopping streets, areas with zero parking costs and areas with a large number of historical sites, the rent gradient is flatter. The vacancy rate is almost twice as high on the edge as in the centre and the share of non-retail land use is one and a half times as high on the edge. These results are in line with our theoretical predictions and robust to various tests we apply.

The Great Recession led to a prolongued negative demand shock in the Netherlands: retail sales dropped by almost 10% in the period 2008-2014. We show that the retail land market reacted as predicted by our theoretical model. Retail rents declined by 20%, and simultaneously, vacancies increased by a factor 1.6. Some 2% of retail properties were transformed to other land use, more so near the edges of shopping areas.

This paper is connected to several strands of literature. First, there is a large body of literature studying urban structure and the interaction between different land uses within a city (see a recent overview in Duranton and Puga, 2014). Many papers use a monocentric city framework in which residential neighbourhoods surround the central business district. A recent example is Combes et al. (2016) who calculate residential land price gradients for different French cities. Lucas and Rossi-Hansberg (2002) develop a theoretical model of a city where the equilibrium patterns of working and housing can vary. Ahlfeldt et al. (2016) build a structural model of internal city structure with many discrete locations that can be used for both, living and working. We are not aware of any studies that focus specifically on retail land use. In this paper we apply a monocentric model traditionally used to describe the residential land market, to explain the distribution of rents and vacancies within shopping areas. Furthermore, we provide new insights into the interaction between residential and retail land uses.

Second, our paper is related to studies that analyse the role of distance in retail location choice. Ushev et al. (2015) show theoretically that despite its non-central location, a suburban shopping mall can win competition from downtown incumbent retailers if the shopping mall developer better internalizes the agglomeration externalities shops exert on one another. Gould et al. (2005) find empirically that shops are ready to pay higher rents for locations on a short distance from an anchor store, to profit from the higher consumer flows it generates. Liu et al. (2016) show that, in tall buildings, retail usually only occupies the ground floor. Transportation costs the consumers have to incur to get to higher floors tend to be prohibitive to locating there. We illustrate that the walking distance to the centre of the shopping area has an effect on retail profits and shop rents.

Third, there is a growing body of literature on the impact of various economic trends and policies on the retail market. Foster et al. (2006) show that high productivity growth in the

American retail sector in the 1990s is largely accounted for by the entrance of large, more productive chain stores and exit of smaller, less productive retailers. Coilion et al. (2015) show that higher unemployment generally leads to reallocation of consumption expenditures to cheaper stores. Cheshire et al. (2011) find empirically that urban planning policies supporting downtown shopping areas at the expense of suburbs lead to welfare costs in terms of lost output in retail and a smaller supply of shops. Koster et al. (2014, 2017) study the positive externalities arising from clustering of shops and suggest that policies stimulating this clustering may be welfare-improving. We use our model to predict how rents, vacancies and land use in a shopping area react to the general decline in demand, and we find support for these predictions in the data.

Finally, there are a few studies analysing the determinants of retail real estate development. Clapp et al. (2015) study the determinants of expansion and contraction of shopping centres and provide an extensive literature review. These studies do not explicitly model the land market, nor do they account for competition for land between different uses, while our paper does.

Our research results are interesting for two reasons. First, we provide new insights into the working of the retail real estate market. Retail occupies an important place in urban space and is an important segment of the economy: In 2015 it accounted for some 10% of the jobs and more than 20% of household expenditures; 20% of trips made had shopping as a motive.

Second, our paper contributes to furthering the understanding of how cities operate and grow. Historically many cities have developed around a shopping centre. A widespread adoption of the car has led to decentralisation of living, working, but also retail. In the US this has resulted in the arisal of 'donut' cities, where empty downtowns hosting vacant shops, are surrounded by residential neighbourhoods.[3] In Europe, policy makers and society at large are concerned lest a similar development should take place. In this paper we discuss how the real estate market in a shopping area reacts to a drop in consumption.

The structure of the paper is as follows. Section 2 presents some stylized facts that inspired our model, and discusses the definition of the centre of a shopping area. Section

[3] Fogelson (2005) observes for the United States that "the decentralization of the department stores is one of the main reasons that the central business district, once the mecca for shoppers, does less than 5 percent of the retail trade of metropolitan areas everywhere but in New York, New Orleans, and San Francisco".

3 introduces the theoretical model, derives empirical predictions and discusses how they will be tested. Section 4 describes the data. Section 5 reports the estimation results for the spatial structure of shopping areas and tests their robustness. Section 6 deals with the effects of the Great Recession and discusses some policy implications. Section 7 concludes.

2 Stylized facts and the definition of the centre

In this paper we document that shopping areas in the Netherlands have a monocentric spatial structure. For this purpose for each shopping area we need to specify its centre. We use different definitions: (i) the spot with the highest density of shops; (ii) the spot with the highest footfall; (iii) the geographical centroid; (iv) a transportation hub most closely located to the geographical centroid.

Figure 1 below illustrates the first definition for 9 shopping areas of different size. For each spot within these areas we calculated the shop density as a weighted average of the number of shops within three radiuses from the spot: 50m, 50-100m and 100-250m: $0.45\text{shops}_{<50m} + 0.35\text{shops}_{50-100m} + 0.2\text{shops}_{100-250m}$. The choice to apply a weighted average of densities on different distances has practical reasons. We experimented with different radiuses. Using only the smallest radius of 50 metre yielded unreasonably high density for tall buildings standing on the edge of a shopping area, while using only the large radius of 250 metre resulted in equal density for all shops located in the same small shopping street. The weighted average allows to avoid these degenerate solutions.

In Figure 1, red balls stand for high density and blue balls stand for low density. Each of the 9 shopping areas in the figure has a pronounced centre, where density is the highest, and a pattern of decreasing densities towards the edge. This monocentric pattern holds for other larger shopping areas too. A simple fixed effect regression[4] of densities on distance suggests a decrease in density of 34% with every additional 100 metre distance from the centre.

Figure 2 shows that rents follow a monocentric pattern too. The figure reports a non-parametric estimate[5] of the dependence between the rents on the y-axis and the distance to the centre of the shopping area on the x-axis. The rents for an average shopping area in

[4] The fixed effects are on the level of shopping areas.

[5] Here and in other non-parametric models we use a kernel regression with a Nadayara-Watson estimator and a Gaussian kernel.

our data are around 500 euros in the centre and fall to some 200 euros on the edge. Using other definitions of the centre yields a similar rent pattern. Indeed, distances to the centre calculated using these other three definitions of the centre have a high correlation with the density-based definition, see Table 1 below.

Figure 1. Shop densities in shopping areas.

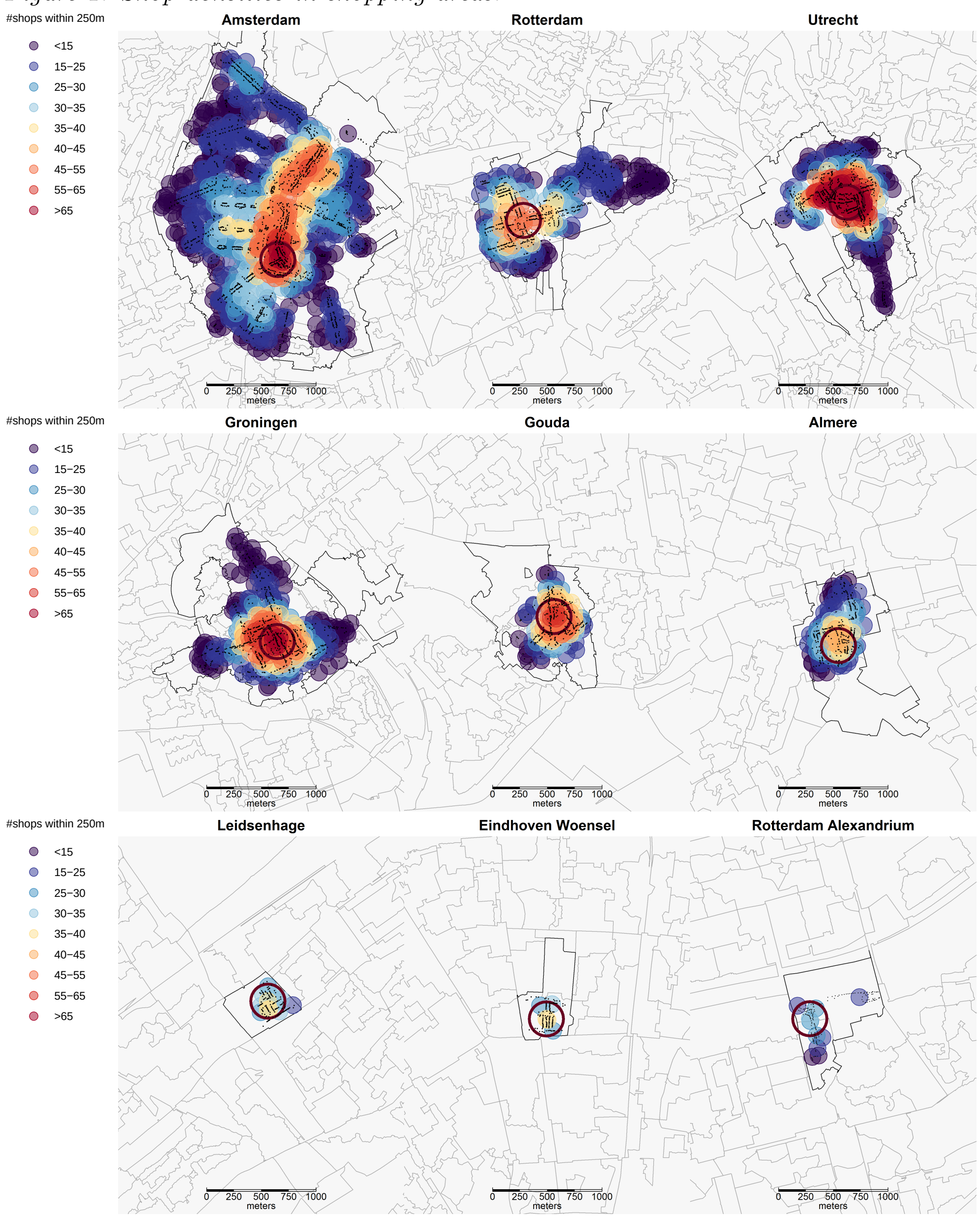


Figure 2. Non-parametric estimates of the rent gradient

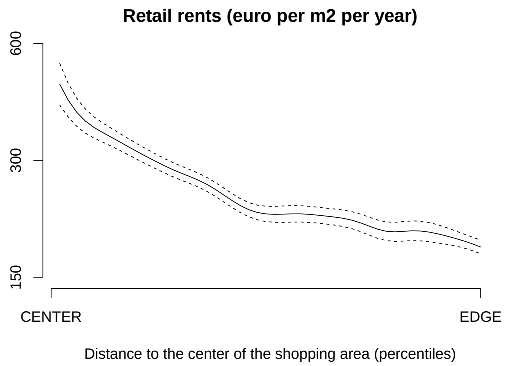


Table 1. Correlations between distances to centre, density-based and other definitions of centre

	highest footfall	geographical centroid	most centrally located transport hub
correlation	0.85	0.85	0.69
#shopping areas with this definition available	121	327	262

3 General framework

We now develop a simple theoretical model that results in the spatial structure of a shopping area described in Figure 2, and study its implications.

3.1 Theoretical model

Our theoretical model rests on the following set of assumptions:

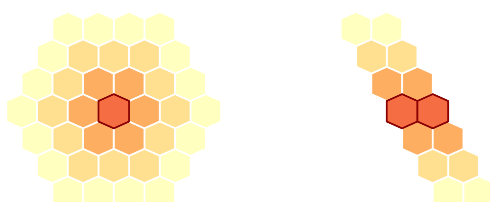
- A shopping area s consists of a number of 'combs ' hosting shops, which are connected in a honeycomb structure. Figure 3 shows two possible forms of this honeycomb: a circle (a shopping centre) and a line (a shopping street).
- The entrance is located in the middle of the honeycomb as illustrated in red in Figure 3. For a shopping centre this central entrance can be thought of as a transport hub (metro station, bus stop) through which people arrive at the shopping area. Alternatively, the central entrance could be a square/crossroad with the highest concentration of shops, that has such a high attractiveness for consumers that they start their trip

there (compare Figure 1). Similarly, for a shopping street the central entrance could be a crossroad with the highest concentration of shops. Let r be the distance from a comb to the center, hence $r = 0$ is the center itself and $r = 0..3$ in Figure 3.

- A consumer visiting a shopping area starts and ends her trip in the centre. Each trip has an exogenously given length k; k is the number of combs visited, including the central comb. During a trip, each comb is visited only once. Every path of length k in shopping area s has the same probability of being chosen.

- Let the number of consumers visiting area s be N_s. Let them all make trips of length k. Then the number of consumers visiting combs at distance r from the centre will be $N_s Pr(r|s,k)$. $Pr(r|s,k)$ is here the probability that a consumer visits a comb located at distance r, conditional on her choice of s and k.

Figure 3. Honeycomb structure; left shopping centre, right shopping street; red combs in the centre are the entrance



The discussed honeycomb structure can be seen as a graph, where combs are nodes and where a visitor follows a simple cycle path of a length k that starts and ends at the central entrance point. Standard software (Python, R) offers algorithms to compute all such possible paths. This allows to calculate numerically the probability $Pr(r|s,k)$. Figure 4 reports this probability for $k = 4, 7, 10, 13$ for a shopping center and a shopping street.

Figure 4. Distance decay in footfall for different lengths of trip k

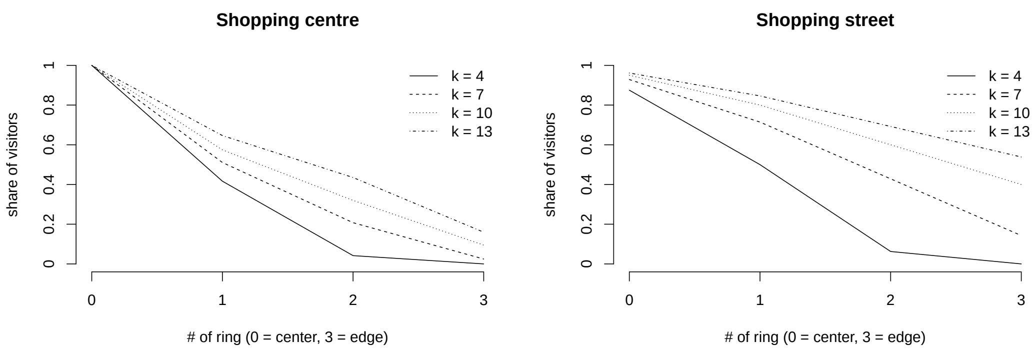


Figure 4 illustrates the distance decay in footfall that is implied by our assumption of a central entrance. The figure has two interesting implications. First, it suggests that shopping areas stimulating longer trips (a higher k) will command a flatter distance decay. Second, for the same length of a trip, a street will have a flatter distance decay than a shopping centre.

Let retail profits and rents be a monotonic function of the footfall. Then the distance decay and the discussed heterogeneity effects will hold for the rents as well. This leads to a testable hypothesis 1 below.

Hypothesis 1. *The distance decay in footfall and rents is ceteris paribus flatter for shopping areas stimulating longer trips and for shopping areas with one-dimensional geometry (shopping streets).*

How can a shopping area stimulate a longer trip? One possibility is to increase the utility of the visit by adding extra amenities to the shopping area. For instance, attractive historical sites, or bars and restaurants can be such amenities. Another possibility is to reduce fixed travel costs, e.g. by offering free parking or by arranging special shuttles between the shopping area and the closest public transport hub. In the next Section we will test Hypothesis 1 on real data.

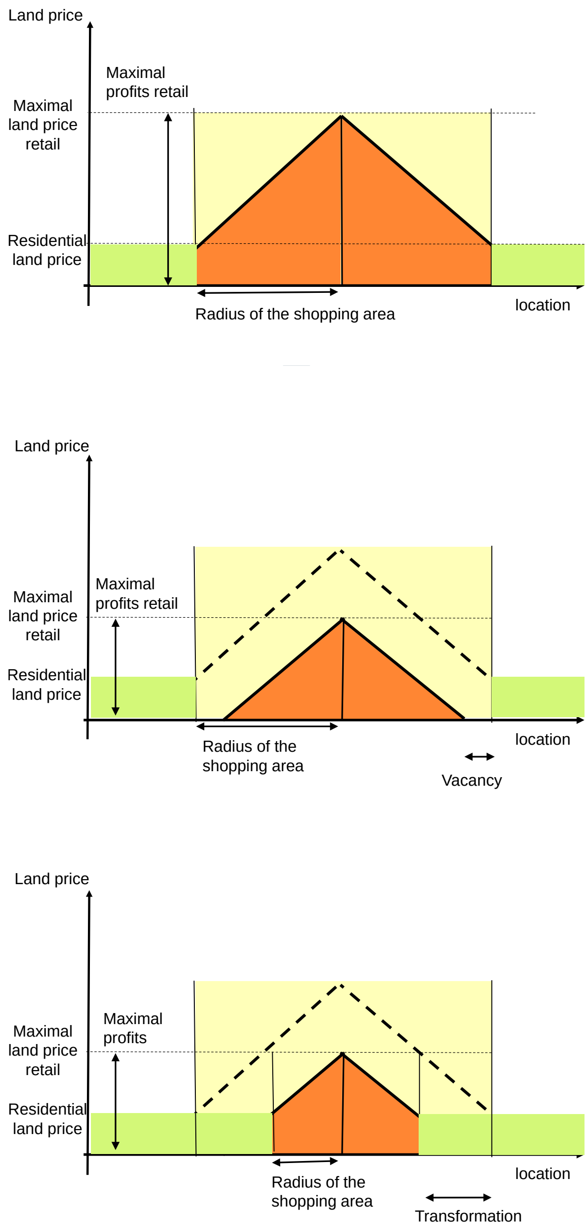
Consider now a shopping area s that is surrounded by residential land use. The land is owned by absentee landlords who extract the profits from tenants (retailers or residents) in the form of land rents. The land is equally suitable for residential and retail use and is assigned to the highest bidder. The residential rent around the shopping area s is fixed and equals R_h.

Figure 5 illustrates the competition between retail and residential land use. In the centre of a shopping area retail rent is higher than the rent of the competing, residential land use, and the land is optimally allocated to retail. Retail rent falls with the distance from the centre. At a certain distance r^* the retail rent becomes equal to the residential rent: $R_{r^*} = R_h$. Distance r^* determines the optimal size of the shopping area. Figure 5 upper panel depicts a shopping area that has an optimal size. Note that the optimal size of a shopping area is the larger the higher the demand for retail products (in our case measured by footfall) and the lower the rent of the competing residential land use R_h. This suggests that changes in the retail demand and/or residential land rents should, in the long run, lead to transformations of land on the edges of shopping area, from retail to residential use or the other way around. As these changes are likely to happen regularly, the edges of shopping areas will tend to have mixed land use. This leads to Hypothesis 2a:

Hypothesis 2a. *Non-retail (mixed) land use concentrates on the edges of shopping areas.*

In the short run, land transformation is not always feasible, for instance due to zoning restrictions. In practice, shopping areas may thus be smaller or larger than optimal. In the first case, the retail bid-rent on the edge is higher than the residential bid-rent and the rent experiences a discontinuous downward jump on the edge of a shopping area. In the second case the retail bid-rent on the edge is lower than the residential bid-rent. If the retail bid-rent is also lower than zero, vacancy arises, see Figure 5 middle panel. In this case the number of consumers visiting the shops on the edge of a shopping area is not sufficient to make these locations profitable even at a zero rent. This leads to hypothesis 2b.

Figure 5. Competition between retail and residential land use; the land market reaction to a fall in demand



Hypothesis 2b. *Vacancies concentrate on the edges of shopping areas.*

In the longer run vacant buildings are likely to be taken over by other land uses which can exploit the land profitably. This is illustrated in Figure 5 lower panel. From this figure we can derive testable predictions concerning dynamic adjustments to negative demand shocks, see Hypothesis 3.

Hypothesis 3. *A negative shock to demand results, in the short run, in a simultaneous fall in rents and a rise in vacancies. In the longer run, retail properties will be transformed into other properties, more so on the edges of shopping areas.*

The derived hypotheses will be tested on real data on rents, vacancies and transformations of land use in the period 2004-2014, including the Great Recession.

3.2 Empirical specification

We use a number of different empirical specifications to test the hypotheses 1 to 3; these are presented in Table 2. The equation number corresponds to the respective hypothesis.

Table 2 Equations to be estimated

		dependent	independent
1a	OLS Footfall	$\ln F_{ist}$	L_{ist}, d_{ist}, I_s
1b	OLS Retail rents	$\ln R_{ist}$	L_{ist}, d_{ist}, I_s, T
2a	Logit non-retail land use	$Pr_{ist}[non-retail]$	$L_{ist}, d^{rel}_{ist}, I_s$
2b	Logit vacant shop	$Pr_{ist}[vacant \vert shop]$	$L_{ist}, d^{rel}_{ist}, I_s$
3	Logit transformation retail to other use	$Pr_{ist}[transformed]$	$L_{ist}, d^{rel}_{ist}, I_s$

Specifications 1a-1b estimate the gradients for footfall (F) and rent (R), where i is a shop located in shopping area s in year t. The explanatory variables include: distance to the centre of the shopping area (d) in metres, structural and locational attributes of the property (L), shopping area fixed effects (I), and, where applicable, a time trend (T).

Structural and locational attributes include the size of the property, its construction period and whether or not the property belongs to a mall. We define malls as the parts of the shopping areas that have been developed according to one plan of the same architect.

These may be indoor or outdoor malls. They often have a single owner or manager. We expect that malls have ceteris paribus higher rent levels and a higher footfall because a single manager can internalise the externalities shops exert on one another (Gould et al., 2005).

We include a number of relevant cross-effects in specifications 1a-b. We expect a flatter distance decay in streets and in shopping areas that stimulate a longer stay due to e.g. free parking or attractive sites. We therefore include cross-effects of distance with: a dummy 1/0 shopping street, a dummy 1/0 free parking and a continuous variable indicating the (log) number of monuments in a 1 kilometre radius from the centre of a shopping area.

Specifications 2a and 2b use logit models to test whether the probability that a property is non-retail and the probability that a shop is vacant are higher on the edge of a shopping area when compared to the centre. The explanatory variables are similar to those used in the OLS with one difference. The distance is now measured on a relative scale 0 to 1 where 0 corresponds to the centre and 1 corresponds to the edge: $d_{ist}^{rel} = d_{ist}/\max_l(d_{lst})$, $d_{ist}^{rel} \in [0, 1]$.

Finally, specification 3 estimates the probability that a property that was a shop at the beginning of the Great Recession was transformed to another use by the end of it. Here again, the distances are measured on a relative scale 0 to 1.

4 Data

We exploit four unique datasets:

(i) A dataset with the characteristics of all the shops in the Netherlands during the time period 2004-2014. This dataset was collected by Locatus, the Dutch market leader in retail information. The following information about each shop is available: size, shop name, address and product category, geographical location (x and y coordinates), whether the shop belongs to a shopping area and if so, to which one, whether the shop is part of a mall and whether it is vacant.

(ii) A dataset BAG (Basisregistraties Adressen en Gebouwen), which includes all the real estate properties in the Netherlands in 2014, containing information on the function (retail, residential, etc.) and size of each property, as well as the functions it had in the preceeding years. This dataset was made available by the Netherlands' Cadastre and Public

Register Agency (Kadaster).

(iii) Two datasets on retail rent transactions. The first one covers the years 2004-2014 and was collected by Strabo, the Dutch specialist in commercial real estate. It contains information on new retail rent contracts that has been made publicly available through newspapers or Internet. Another database covers the years 2009-2014 and was collected by the real estate company Jones Lang Lasalle (JLL). It contains the Strabo rents 2009-2014 as well as not publicly available new retail rent contracts that were signed by JLL clients during this period.

Table 3 Data selection shopping areas

	Locatus		JLL	Strabo	BAG
	shopping areas	shops	rent trans.	rent trans.	all properties
	2004-2014, average/year		2009-2014	2004-2014	2014
initial database		104255	6979	6224	9 mln
located within shopping areas	2607	79975			
>=25 shops, not specialized	447	50342			
rents available JLL	327	43816	3701		242806
rents available Strabo	368	46575		4803	

Table 3 describes our data selection process. We are interested in properties located in shopping areas. The geographical definition of the shopping areas was done by Locatus and is based on their knowledge of the retail market and their expert judgement. From some 104 thousand shops in the Netherlands, around 80% are located within shopping areas. The rest are small dispersed retail points, e.g. a bakery on the corner of a residential block. Because of the poor availability of the rent data for small shopping areas, this paper focuses on shopping areas with more than 25 shops. We ensure that these are compact by removing stores on the edge if they are located at a distance from the main cluster. We exclude specialized shopping areas such as furniture malls. Applying these selection criteria reduces the number of shopping areas in our database from the original 2600 to some 450 and the number of shops from 80 thousand to 50 thousand. Finally, the number of shopping areas with known rents is some 300.

Figure 6 reports the location of the shopping areas in our selection, by municipality. The four largest cities, Amsterdam, Rotterdam, The Hague and Utrecht have the largest concentrations. The south of the country has relatively large concentrations too. Relatively few shopping areas are located in the periphery. By and large, the distribution of the shopping areas follows the distribution of the population.

Figure 6. Location of the shopping areas

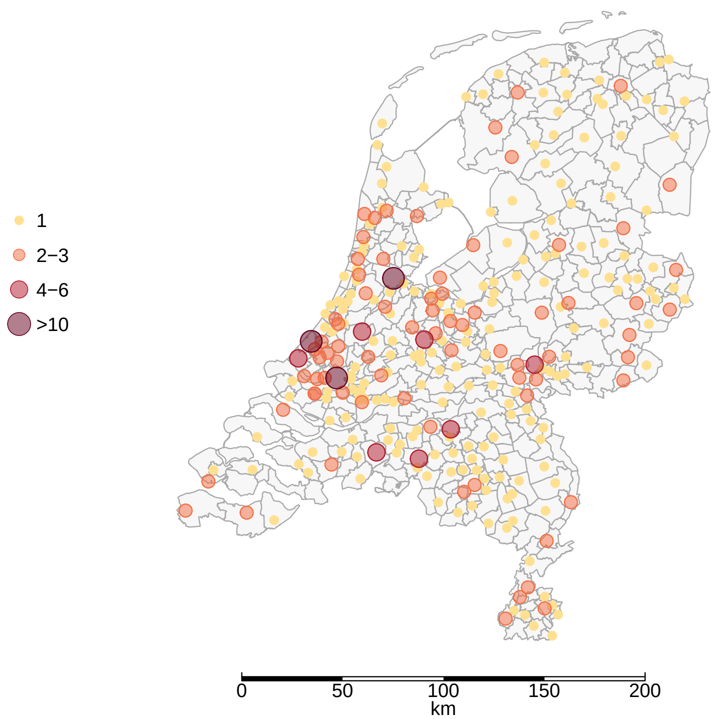


Table 4 reports the descriptive statistics of the data. An average shop in our data has a floor space of some 200 m^2, is located at a distance of 200 metre from the centre of its shoping area, has 30 other shops within a 250 metre radius and 300 monuments within a 1 kilometre radius. An average shop has a probability of 10% to be vacant. Vacant shops are somewhat smaller and are located in areas with fewer touristic attractions (fewer monuments).

Table 4 Descriptive statistics shops

	All properties		Shops		Vac.shops		Shops with known rents			
	BAG		Locatus		Locatus		JLL		Strabo	
	2014		2014		2014		2009-2014		2004-2014	
variable	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.
Dependent variables										
footfall (thous. visitors/day)[6]	-	-	12.15	10.58	7.71	6.79	11.83	11.53	11.03	10.29
rent (euro/m^2)	-	-	-	-	-	-	301.62	265.08	277.37	196.58
# shops within 250m	24.69	13.71	29.85	15.66	27.62	14.36	32.80	17.14	33.25	17.48
vacant shop 1/0 (in %)	-	-	10.61		-	-	-	-	-	-
non-retail property 1/0	0.80		-	-	-	-	-	-	-	-
Structural charact.										
m2	160.94	354.75	191.79	429.36	172.69	238.76	195.85	275.15	217.89	257.67
construction year <1900	0.21		0.18		0.13		0.21		0.19	
construction year 1900-1944	0.28		0.28		0.26		0.28		0.28	
construction year 1945-1959	0.06		0.08		0.08		0.08		0.09	
construction year 1960-1979	0.10		0.15		0.14		0.10		0.12	
construction year 1980-1999	0.21		0.17		0.17		0.15		0.14	
construction year >=2000	0.11		0.08		0.07		0.07		0.07	
construction year unknown	0.03		0.08		0.17		0.11		0.12	
Location charact.										
dist. centre shopping area (m)	292.30	260.59	208.73	197.67	205.10	159.86	226.87	186.42	211.77	173.53
mall 1/0	0.10		0.23		0.23		0.17		0.19	
shopping street 1/0	0.14		0.10		0.08		0.09		0.08	
# monuments within 1km	370.0	819.56	274.03	660.04	163.42	374.49	330.34	643.20	248.04	467.38
free parking 1/0	0.19		0.25		0.21		0.16		0.19	
#properties	242806		46162		4898		3701		4803	

Only 20% of the properties in our shopping areas are retail. The rest have another function, mainly residential. The intuition for this, at the first glance, surprising result is

[6] Footfall is available for a sample from the dataset, including the central parts of the larger shopping areas.

as follows. First, small retailers often live above their shops. Second, many of our shopping areas are located in cities where multi-storey buildings are common. Liu et al. (2016) show that retail is concentrated on the ground floors (plints) of these buildings and leaves other floors to other uses.

For some 10% of the shops we know the rents at some moment in time, the average rent being 300 euros per m^2 retail space per year. Shops with known rents do not significantly differ on observables from the average shop. Footfall is available for 121 most visited shopping areas and data on vacancy, non-retail status and density are available for all the shops. Footfall is defined as the number of passers-by counted in front of a shop on a Saturday outside of holiday periods.

Our data provide information on a number of location characteristics of the shops. First, 10% of the shops are located in shopping streets. A street is a one-dimensional shopping area and is defined based on the classification made by the retail property expert Locatus. Some 25% of the shops lie in shopping areas with zero parking costs. The information on the parking costs was provided by the Dutch Ministry of Transportation. Around 20% of the shops belong to malls; the definition of a mall is again based on a classification by Locatus. A mall is defined as a part of the shopping area that has been developed according to one plan of the same architect; a mall is usually smaller than the shopping area to which it belongs.

5 Estimation results spatial structure

In this section we test hypotheses 1 and 2 about the spatial structure of the shopping areas.

5.1 Distance decay in footfall and rents

Figure 2 provided non-parametric support for a distance decay in rents using raw data. Table 5 reports the results of estimating the distance decay for footfall and rents parametrically (specifications 1a-b from Table 1). Here we use shopping area fixed effects and include various regressors to account for observed and unobserved heterogeneity between shops. To account for a possible non-linearity of the distance effect we include it as a second order polynomial. In the regression for footfall we do not include the floor space as an explanatory variable, due to the possible endogeneity of this regressor. We account for heterogeneity between shopping areas by including cross-effects of distance with shopping area characteristics.

Table 5 Footfall gradient and rent gradient

	Footfall (log) thous.pers./day 2014 (i)		Rents JLL (log) euro/m2/year 2009-2014 (ii)		Rents Strabo (log) euro/m2/year 2004-2014 (iii)	
variable	coef	t-val	coef	t-val	coef	t-val
dist.to centre shopping area (100m)	-0.401	(6.33)	-0.234	(7.20)	-0.149	(4.76)
dist squared	-0.002	(0.48)	0.005	(1.87)	0.003	(1.10)
cross-effect distance x type shopping area						
shopping street (1/0) [a]			0.095	(3.19)	0.082	(3.28)
log monuments within 1km	0.045	(2.81)	0.013	(1.77)	0.004	(0.69)
zero parking cost (1/0)	-0.073	(0.94)	0.131	(4.35)	0.038	(1.48)
floor space (log)	0.093	(8.76)	-0.301	(22.43)	-0.382	(26.79)
property is part of a mall (1/0)	0.162	(2.38)	0.306	(7.97)	0.167	(3.61)
construction period fixed effects	YES		YES		YES	
year fixed effects	NO		YES		YES	
shopping area fixed effects	YES		YES		YES	
R^2 within	0.132		0.214		0.284	
# observations	23509		3701		4803	
# fixed effects	121		327		368	

[a] Information on footfall in shopping streets is largely missing in our data.

Coefficients of the structural and locational characteristics of a shop are in line with the intuition. Larger shops command lower rent by m^2 floor space and attract a higher footfall; properties located within malls have higher rents and higher footfall.

The rent gradient (columns (ii) and (iii)) is negative and significant. On average, the marginal distance decay at 100 metre distance from the centre is -15%, the effect becoming flatter towards the edge. Heterogeneity between shopping areas appears to be sizable.

Shopping streets, areas with free parking and areas with many monuments have a flatter rent gradient, as predicted by the theoretical model. Table 6 reports the marginal rent gradient for a number of specific shopping areas from our data. For example, the marginal rent gradient at 100 metre from the centre is -5% in a shopping centre with median monuments and free parking. It amounts to -22% in a shopping centre with paid parking and few monuments. A street with paid parking and median monuments commands a distance decay of -9%. The two datasets on rents we use (Strabo and JLL) give similar results; this provides us with additional security about the insights.

The footfall gradient has a similar behaviour to the distance decay in rents. It is negative and significant. It is flatter in shopping areas located in attractive sites.

Table 6. Marginal effect rents at 100 metre from the centre, by type of shopping area

average shopping area	-0.150
street, no free parking, median monuments	-0.092
no street, free parking, median monuments	-0.056
no street, no free parking, 90 percentile monuments	-0.158
no street, no free parking, 10 percentile monuments	-0.218

Table 7 provides robustness checks, using the three alternative definitions of the centre of a shopping area introduced in Section 2. We provide results for models without heterogeneity. All alternative definitions yield a significant negative distance decay. The value of the gradient is not significantly different from the baseline when the centre is defined as a geographical centroid or as the spot with the highest footfall. The gradient is, however, twice as flat when a transportation hub (bus/tram/metro) is taken as the centre. A possible reason for a less pronounced effect is that the core of a shopping area is often a pedestian zone so that public transport stops have to be located closer to the edges.

Table 7. Robustness of the rent gradient to alternative definitions of distance								
	baseline		highest footfall		geographical centroid		centrally located transport hub	
	coeff	t-value	coeff	t-value	coeff	t-value	coeff	t-value
# shopping areas alternative definition	327		121		327		262	
rent gradient (x 100 metre)	-0.163	(7.23)	-0.214	(9.17)	-0.192	(8.26)	-0.074	(2.83)
squared rent gradient	0.006	(3.74)	0.009	(3.87)	0.008	(3.12)	-0.002	(0.79)

5.2 Vacancy and non-retail clustering on the edge

Figure 7 reports a non-parametric estimate of the distance effect for vacancy and non-retail land use using raw data. The vacancy rate on the edge is almost two times higher and the share non-retail use one and a half times higher than their respective values in the centre. These results are in line with our model: closer to the edge of a shopping area, land use gets more mixed and more vacancy appears. Table 8 reports the results of a logit estimation for both variables. The dependent variable is the probability for a property to be vacant respectively non-retail. The distance coefficient is in both cases positive and highly significant, in line with the non-parametric results.

Figure 7. Distance effect in vacancy and non-retail land use

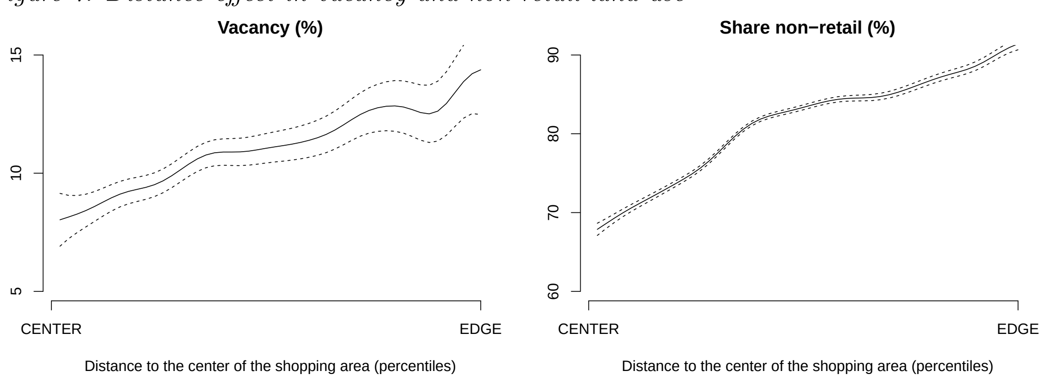


Table 8 Logit distance effect vacancy and non-retail use

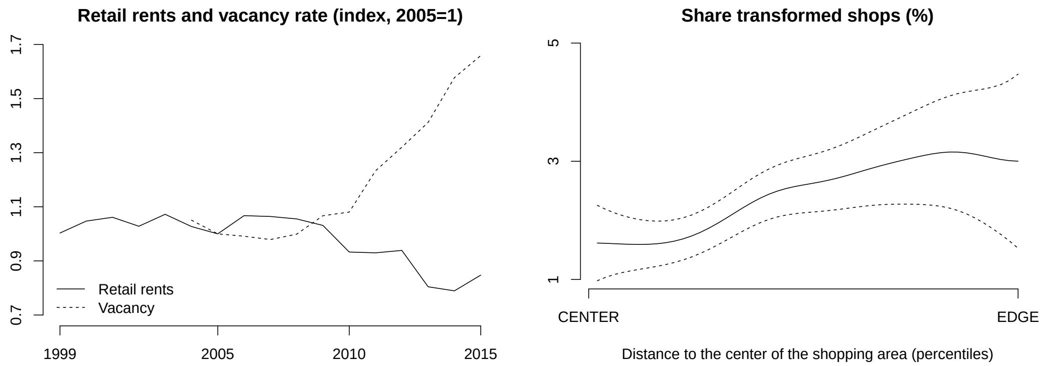
	Vacant		Non-retail use	
	2014		2014	
	coef	t-val	coef	t-val
centile dist.to centre shopping area (/100)	0.669	(9.79)	1.868	(65.37)
floor space (log, m^2)	0.047	(2.83)	-0.724	(103.85)
part of a mall cluster	0.054	(1.04)	-1.216	(55.85)
construction period fixed effects	YES		YES	
shopping area fixed effects	YES		YES	
# observations	46162		242806	
# shopping area clusters	327		327	

6 Dutch retail after the Great Recession

In this Section we test hypothesis 3. During the Great Recession 2008-2014 the Netherlands was hit by a large and prolonged negative consumption shock. According to the data of Statistics Netherlands, retail sales decreased by some 10% in this period. Our model predicts that such a drop in consumption would result in: (i) a simultaneous drop in rents and a rise in vacancies, (ii) transformations from retail to other land use, especially on the edges of shopping areas.

We run an OLS rents and a logit vacancy (specifications 1b and 2b in Table 1) again, for the years 2004-2014. Figure 8 left panel shows the year fixed effects. The behaviour of the rents and vacancies is in line with the predictions of our theoretical model. Before the Great Recession neither rents nor vacancy levels changed much. Between 2008 and 2014 rents fell by 20%, and simultaneously, vacancies rose by a factor 1.6.

Figure 8. Left: rents dropped and vacancies rose in the Great Recession. Right: transformations of shops to other uses are more likely on the edge.



We turn now to the transformations from retail to another land use. We define transformations as properties that had a retail function in 2010 and another (or mixed) function in 2016. We were able to collect data on transformations for 49 shopping areas located in 26 larger Dutch municipalities. Appendix A reports the descriptive statistics of this sample. It covers some 25% of the data used in the rest of this paper and is representative if judged by the observables we use in the estimations.

Some 2% of the properties that were retail in 2010, were transformed to another use in the 6 years following. Figure 8 right panel presents a non-parametric estimate of the probability of a shop being transformed as a function of its location within a shopping area. In line with the predictions of our model most transformations took place on the edges. Table 9 reports the results from a formal logit model explaining the probability of being transformed from the structural characteristics of the shop and its location. Here we account for unobservable differences between the shopping areas by including shopping area fixed effects. The distance effect is positive and significant. In line with the intuition, larger retail properties and properties located within malls have a lower probability of being transformed.

Table 9 Distance effect in transformations

	Logit transformation from retail to other use	
variable	coef	t-val
dist.to centre shopping area (centile/100)	1.067	(3.40)
floor space (log, m^2)	-0.116	(1.32)
part of mall	-1.656	(3.24)
dummies construction period	YES	
shopping area fixed effects	YES	
# observations	9926	
# fixed effects	49	

The retail vacancy rate in the Netherlands is at the moment 10%. As figure 8 shows it has not been this high for the last 13 years. There are concerns in society that a part of this vacancy might be structural and will not be eliminated by the ongoing economic recovery. One of the reasons is the substitution of brick-and-mortar shopping for online shopping, resulting in lower demand for retail properties. Our theoretical model (Figure 5) suggests indeed that if the drop in consumer demand is permanent, then there may be locations on the edges of shopping areas that become unprofitable for retail at any level of rent; these are likely to be taken over by other competing land uses. In the above discussion we have shown that such transformations have indeed taken place in the Dutch real estate market.

Is it likely that the years to come will result in more transformations? A necessary condition for a transformation is that a location is more profitable for other land use than for retail (see Figure 5 last panel). Transformations are thus most likely to happen in locations where demand for retail land has dropped, but demand for land for competing uses is high. Examples are locations in or near larger cities, on the edge of the downtown or in shopping streets. In areas where the overall demand for land is declining, for instance due to the declining population, the transformation potential will likely be low. Applying our model to calculate the transformation potential in specific shopping areas is a possible direction for future research.

7 Conclusion

This paper is the first to study theoretically and empirically the land use in urban shopping areas and the competition between residential and retail land in a city. We have developed and tested econometrically a model describing the structure, floor rents and occupancy rates in different shopping areas including both downtowns, as well as shopping streets and districts. We have shown that the spatial structure of all these shopping areas resembles that of a monocentric city. It features one pronounced centre where the level of rents is the highest. Rents decrease with some 15% with every 100 metre extra distance from this centre, the effect becoming flatter towards the edge. In shopping streets, areas with zero parking costs and areas with a large supply of historical sites the rent gradient is flatter. Near the edge of a shopping area rents are the lowest and there is a clustering of vacancies and non-retail land use. Rents and occupancy rates on the edges of shopping areas are most sensitive to changes in economic conditions.

We have exploited the prolonged drop in consumption during the Great Recession in the Netherlands to provide additional support for our model. The model predicts that a negative demand shock should lead to a simultaneous drop in rents and rise in vacancies and, in the longer run, to transformations from retail to other land use, mostly on the edges of shopping areas. This is exactly what we see in the data. During 2008-2014 in the Netherlands consumption of goods and retail sales dropped with 10%. Retail rents declined in the same period with 20%, and simultaneously, vacancies increased by a factor 1.6. Some 2% of retail properties were transformed to other land use, more so near the edges of shopping areas.

Our insights are especially interesting in the light of the recent developments in the market of retail. Demand for brick and mortar shopping has been decreasing in recent years, due to the Great Recession and the rise of online retail. It is likely that a part of this effect is structural. Our model suggests that a negative shock in demand necessarily leads to smaller shopping areas as some locations on the edges become unprofitable for retail use. In regions and locations with high enough demand for land, contraction of the shopping areas can be achieved by market forces, as a result of transformation of retail land to other use. In declining cities and regions, this transformation is less likely to happen by itself and public policy may be needed to prevent empty spaces in downtowns.

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Appendix A. Descriptives data transformations

Table A1. Descriptive statistics transformations

variable	mean	st.dev.
# shops within 250m	32.63	16.48
m2	242.01	411.31
construction year <1900	0.22	
construction year 1900-1944	0.36	
construction year 1945-1959	0.07	
construction year 1960-1979	0.11	
construction year 1980-1999	0.16	
construction year >=2000	0.05	
construction year unknown	0.02	
dist. centre shopping area (m)	232.86	171.27
mall 1/0	0.13	
shopping street 1/0	0.12	
# monuments within 1km	265.64	296.42
free parking 1/0	0.10	
#properties	9926	

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