The urban economics of retail

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22 December, 2022

Abstract

Using property-level data from 327 larger shopping areas in the Netherlands, we show that the spatial structure of a shopping area resembles a monocentric city in miniature. Just like a monocentric city, a shopping area has a pronounced center where the rents are the highest and the vacancy the lowest, and a negative retail rent gradient from this center to the edges. The average retail rent gradient is −20% per 100 meter distance, and the vacancy odds are twice as high at the edge as in the center. In a simple model of land market competition, we illustrate how the negative retail rent gradient helps tackle the adverse consequences of structural drops in retail demand.

JEL Codes: L81, R13, R3, R4

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

1 Introduction

Retail land use plays an important role in cities, next to living and working. In European countries and Japan there is on average 0.5 square meter retail space per capita, in North America this figure is four to five times larger (Statista, 2022).[1] Retail mostly concentrates in cities. Larger cities house ten and more shopping areas, located not only in the downtowns but also in most urban neighbourhoods.[2] Thus, in various parts of the city, retail competes for land with other land uses. Yet, urban economics has so far mainly focused on the land market for housing and - more recently - business premises (see e.g. Combes et al., 2019, Ahlfeldt et al., 2016 and the references therein). Studies of retail land use are scarce.[3] We aim to fill this gap.

Our paper exploits a rich dataset with shop-level observations from the Netherlands to study land use in shopping areas and the competition between residential and retail land in a city. The stores in our data comprise 40% of the country's total retail. They are located in 327 larger shopping areas situated in some 200 cities, thus, on average we have 1.5 shopping area per city. The shopping areas therefore include both, downtown shopping centra and a large number of non-centrally located shopping districts and streets. The average shopping area in our data has 130 shops.

We start by documenting empirically that, in terms of the spatial structure, shopping areas resemble *monocentric cities* in miniature. Within each shopping area one pronounced *centre* can be distinguished, where the number of visitors (footfall) is the highest and the rental levels are the highest. The footfall and the rents decrease monotonically from this center towards the edges, while the vacancy increases. We show that this holds for both, downtown and non-central shopping areas, and for both, shopping districts and shopping streets. We also show that, in all these shopping areas, the residential rent gradient is ten to twenty times flatter than the retail rent gradient. [4] Based on this empirical insight and using a simple land market model, we then derive and test a number of implications of the distance decay in retail rents for the competition between the residential and the retail land use in a city. We consider cities with several shopping areas and argue that: (i) this competition determines endogenously the size of the shopping areas in a city; (ii) it helps the shopping areas to adjust to demand shocks such as e.g. brought about by the Great Recession of the late 2000's, the rise of the web shopping, and, more recently, the Covid. Finally, we provide insights into possible mechanisms behind the negative retail rent gradient and the heterogeneity in its slope.

A number of challenges needs to be solved in the empirical work. First, to correctly estimate and interpret the rent gradients, we need to geographically pinpoint the location of the center of the shopping area. Because there exists no widely accepted unambiguous definition of this center, we suggest and apply three alternative approaches to it, which are based on (i) the highest density of shops, (ii) the geographical centroid of the area, (iii) the highest footfall. We show that the results stay

[1] Liu et al. (2018) shows that retail properties predominantly sit on ground floors of the buildings, so retail *space* and retail *land use* are highly correlated. In this paper, we use the terms *retail space* and *retail land* interchangeably.

[2] Our term 'shopping area' refers to a variety of retail concentrations including: a downtown, a shopping street or district, a mall, etc. These shopping areas differ in character (e.g. neighbourhood – subregional – regional character) and, correspondingly, in the number of shops they house and the trade area size. See ISC Research (2017), Locatus (2016) for shopping area classifications in the US respectively the Netherlands.

[3] There is a small literature on location choice of shops, see Ushev et al. (2015), Gould et al. (2005), Koster et al. (2019), Liu et al. (2018). These authors do not make conclusions about the urban land use however.

[4] Some 80% of the properties in Dutch shopping areas is non-retail, see also Koster et al. (2019).

robust to choosing any of these definitions. Second, for the downtown shopping areas one might be concerned that the shopping area gradient and the monocentric city gradient coincide. To rule out this worry, we argue that the monocentric city distance decay is nowadays driven by rapid transportation modes like car or metro and thus manifests itself on much larger distances than the 500x500 meter area a median shopping area in our data covers (compare e.g. the residential rent gradients from Combes et al., 2019). We find support for this argument by estimating a rent gradient for the dwellings located in our shopping areas, which appears to be ten to twenty times flatter than the retail rent gradient.

This paper exploits longitudinal property-level data from different sources. To estimate the rent gradients, we use a hedonic price regression. We exploit data on new retail rent contracts signed during 2004-2017 and data on residential sales between 2009 and 2018. To estimate the gradients in vacancy and footfall, we make use of a dataset containing property characteristics and the vacancy status for the whole universe of Dutch shops, in 2014. To get insight into how shopping areas adjust to the changes in consumer demand, we use 2010-2016 (the aftermath of the Great Recession) data on the transformations of the retail properties into residential use. These data are also on the property level and available for some 30 middle-large cities. Further, data on shopping area characteristics such as the type of the area (downtown, non-central, street), availability of free parking, availability of cultural amenities, are exploited to get insight into the distance decay heterogeneity and its driving forces.

This paper is connected to several strands of literature. First, there is a large body of literature studying the urban spatial structure and the interaction between different land uses within a city (see e.g. an overview in Duranton and Henderson, 2014). Combes et al. (2019) calculate residential land price gradients for different French cities and Ahlfeldt and Wendland (2011) for Berlin. 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 the internal city structure with many discrete locations that can be used for both, living and working. We are not aware of studies that focus on retail land use. In this paper we estimate a retail rent gradient for urban shopping areas (either central or non-centrally located), and study empirically the spatial structure of these areas. Furthermore, we provide new insights into the interaction between residential and retail land uses.

Second, our paper is related to the works that analyze 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 is able to internalize 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. Koster et al. (2019) confirms that shops experience significant positive externalities from locating close to each other. Liu et al. (2018) 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 for locating there. We argue that the distance to the center of a shopping area has an effect on retail profits, shop rents and vacancies.

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. Coibion et al. (2015) find that higher unemployment generally leads to reallocation of consumption expenditures to cheaper stores. Sanchez-Vidal (2017), Sadun (2015), Haskel and Sadun (2012), Cheshire (2015), Shivardi and Viviano (2010), Bertrand and Kramarz (2002) study the effects of the retail planning regulations in different countries and show that these can have a significant adverse impact on the sector, in terms of lower productivity, smaller number of stores, higher consumer prices. Koster et al. (2014, 2019, 2021) suggest that policies stimulating shop clustering may be welfare-improving because they allow to internalize agglomeration benefits in retailing. We use our model to discuss how the real estate market in a shopping area responds to a drop in consumer demand.

Finally, there are a few studies analyzing the determinants of retail real estate development. Clapp et al. (2014) study the determinants of the expansion and contraction of shopping centers 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 study provides relevant insights for real estate practitioners and local authorities. Brick-and-mortar retail is melting down in many countries, driven by various external developments and the associated shifts in consumer behavior. Empty stores in shopping areas are an eyesore and they impose negative externalities on neighboring retailers (e.g. Koster et al., 2019). While these developments are directly connected to the functioning of the land market, they have not been extensively studied from a land use perspective. Our paper fills this gap. We suggest an explanation of how the structure of the land market in shopping areas can help tackle structural demand shocks.

The structure of the paper is as follows. Section 2 describes the retail real estate in Dutch shopping areas and the data we use. Section 3 introduces an analytical model, derives empirical predictions and discusses the empirical strategy. Section 4 reports the estimation results and tests their robustness. Section 5 discusses the policy implications. Section 6 concludes.

2 Shopping areas: background and analytical framework

2.1 Spatial structure of larger shopping areas

We define a shopping area as a geographically demarcated retail cluster. Locatus – a company that specializes in longitudinal property-level information on the universe of Dutch shops – distinguishes some 2600 shopping areas in the Netherlands.[5] Some 80% of the stores in the Netherlands is located within these areas, the other 20% is stand-alone retail. For the purposes of this paper we are interested in the spatial structure of the shopping areas. Therefore we select larger areas – those with 25 shops or more – and drop specialized areas (like e.g. furniture malls). Further we require that information about retail rents in an area is available.[6] Applying these selection criteria results in 327 shopping areas, which contain a total of 46 thousand shops (40% of the country's retail). The sample includes downtown retail, shopping streets and non-centrally located shopping districts. [7]

[5] The boundaries of the areas have been defined based on the expertise of Locatus.
[6] See Section 2.2 Data description. Where possible, we will check robustness of our results for inclusion of shopping areas with unknown rents.
[7] A downtown shopping area lies in the downtown of a city of a town. A shopping street is a one-dimensional shopping area not being a downtown. A non-central shopping area lies outside of downtown and is not a street.

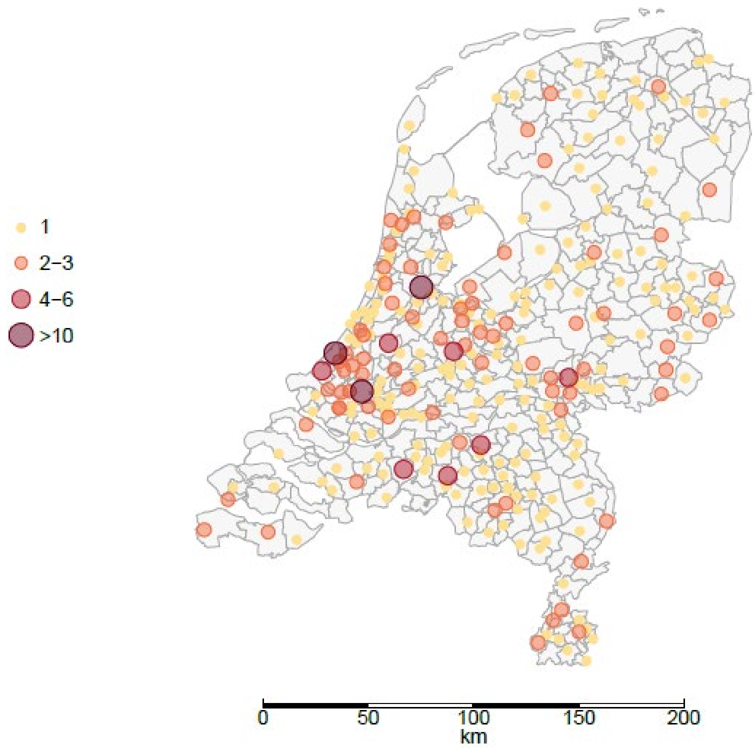
Table 1 reports the described selection steps and Figure 1 shows the spatial distribution of larger shopping areas in our sample across the country. Three top Dutch cities house more than 10 shopping areas each, while most larger towns have two or three shopping areas. By and large, the distribution of the shopping areas follows the distribution of the population.

Table 1: Data selection shopping areas

	# Shopping areas	# Shops
(i) Universe of Dutch shops		104,255
(ii) Located within shopping areas	2606	79,974
(iii) Areas > =25 shops, not specialized	446	55,792
(iv) rents available JLL	327	46,162
(v) rents available Strabo	383	47,970

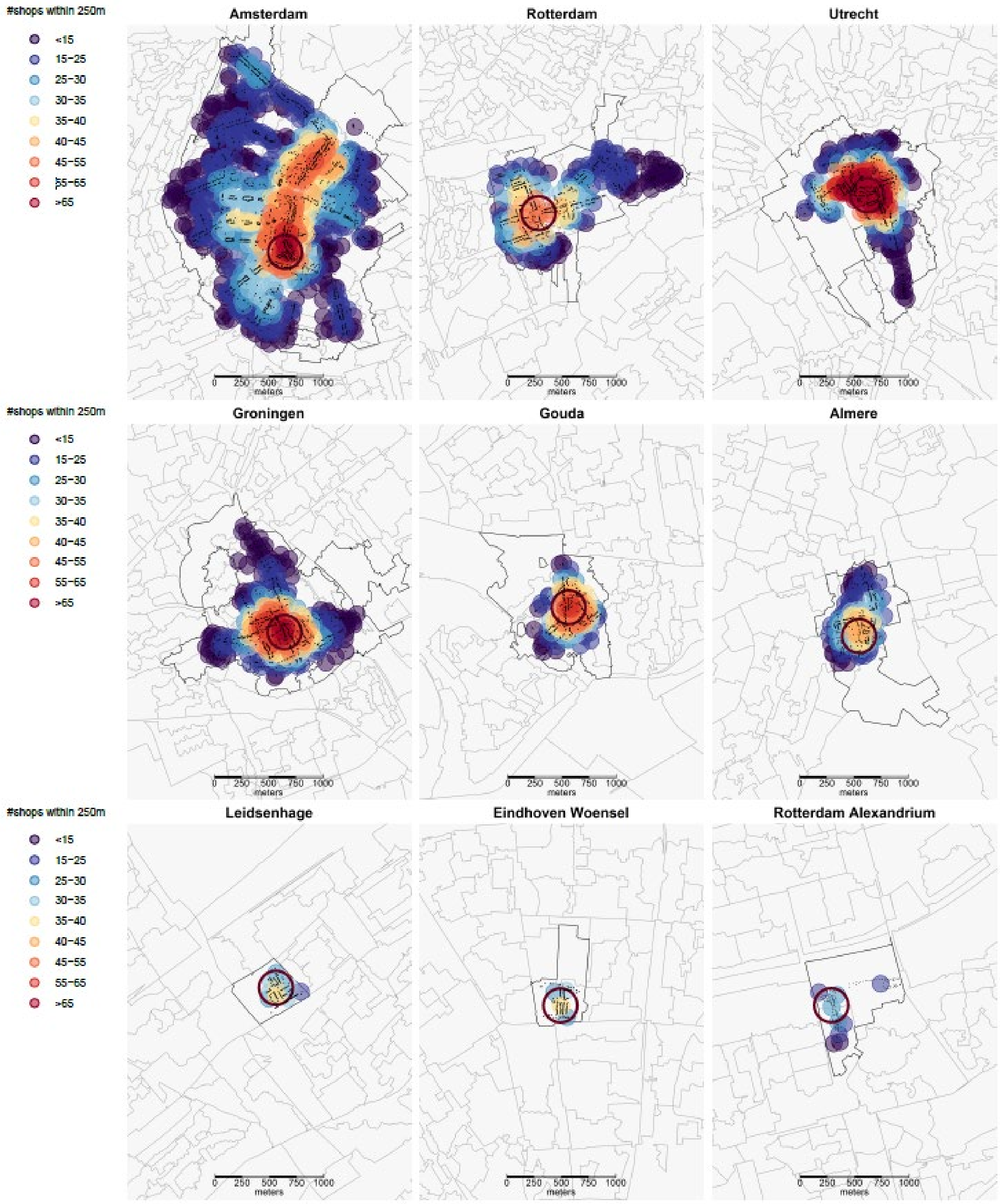
Notes: The selection is done based on the Locatus database containing property-level information for the whole universe of Dutch shops. Datasets (iv) will be used in the main analysis, data (iii) and (v) will be used in the robustness checks.

Figure 1: Number of shopping areas by municipality



Notes: The Figure is based on the Locatus (2014) database containing geocoded property-level information for the whole universe of Dutch shops. We drop shopping areas containing fewer than 25 shops, specialized areas like furniture malls and also areas for which information on rents is unavailable. The resulting sample contains 327 shopping areas.

Figure 2: Shop densities in shopping areas

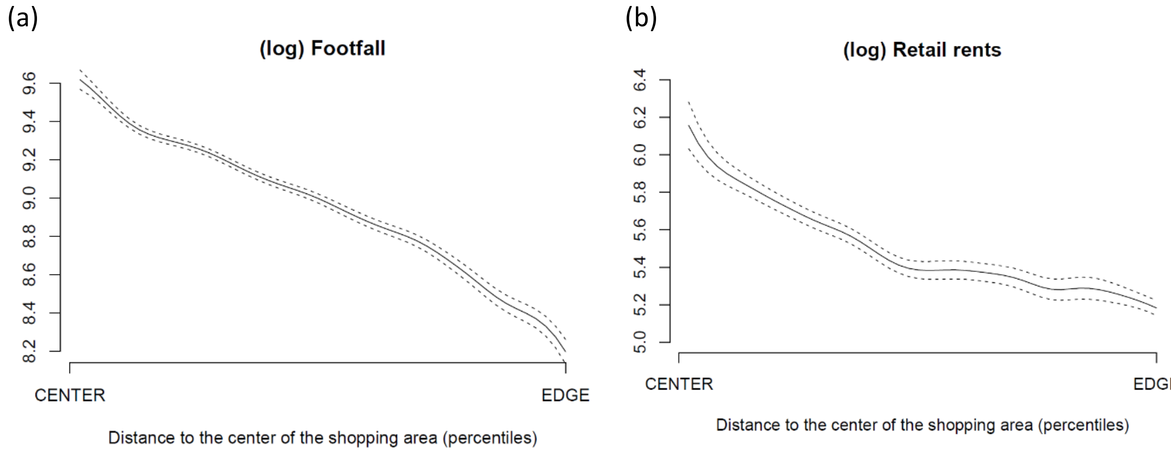


Notes: The Figure is based on the Locatus (2014) database containing geocoded property-level information for the whole universe of Dutch shops. For each shopping area in the Figure, shopping densities at the block level are depicted, calculated as a weighted average of the number of shops in three radiuses from the block centroid: $\alpha_1 shops_{[0m,50m)} + \alpha_2 shops_{[50m,100m)} + \alpha_3 shops_{[100m,250m)}$ with α_1 = 0.45, α_2 = 0.35, α_3 = 0.2.

To get a first insight into the spatial internal structure of our shopping areas, we calculate and depict the store densities by six-digit postcode.[8] To do this, for each postcode centroid, we compute a weighted average of the number of non-vacant shops within three radiuses: [0m,50m), [50m,100m) and [100,250m).[9] Figure 2 reports the resulting densities for 9 shopping areas of different size and type. The reddish bubbles stand for high density and the bluish bubbles stand for low density. What immediately catches the eye is that each of the 9 shopping areas in the figure has a pronounced center, where density is the highest, and a pattern of decreasing densities towards the edge. This pattern holds for other shopping areas in our data too, including non-central districts and streets. Running a simple fixed effect regression suggests an average decrease in shop density of 34% with every additional 100 meter distance from the center of the shopping area. [10, 11]

Several mechanisms may be responsible for the shopping density decrease towards the edge of shopping areas: (i) increasing number of non-retail properties, (ii) increasing shop vacancy rate or (iii) lower density of buildings altogether. In the next section's analytical framework we show that (i) and (ii) can arise due to competition between retail and residential land use in a city.

Figure 3: Non-parametric estimates of the (log) retail rent and (log) footfall gradients



Notes: Panel (a) is based on the Locatus (2014) database containing geocoded property-level information for the whole universe of Dutch shops. Panel (b) exploits data on the new rent contracts 2009-2014. The K-kernel is used.

[8] A six-digit postcode is a small statistical unit, containing on average some 20 addresses (a street).

[9] The following formula is applied: $\alpha_1 shops_{[0m,50m)} + \alpha_2 shops_{[50m,100m)} + \alpha_3 shops_{[100m,250m)}$. The choice to use a weighted average of densities within different radiuses has practical reasons. We experimented with different values of the α. Using only the smallest radius of 50 meter (α_1 = 1, α_2 = α_3 = 0) yielded unreasonably high density for tall buildings standing at the edge of a shopping area, while using only the large radius of 250 meter (α_1 = α_2 = 0, α_3 = 1) resulted in an equal density for all shops located in the same small shopping street. The weighted average allows to avoid these degenerate solutions. In this paper we use the values α_1 = 0.45, α_2 = 0.35, α_3 = 0.2 attaching a somewhat higher weight to the density in the direct vicinity.

[10] We define the centre as the five-digit postcode with the highest density of shops. If there are two or more postcode where the density equals the maximum value, the postcode closer to the geographical centroid of the area is assigned as center.

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

Koster et al. (2019) documents a positive relationship between the shop density, footfall (number of visitors passing the shop) and the retail rents. Therefore we can expect a negative distance decay in visitors and rents as well. Non-parametric estimates for both variables are reported in Figure 3. They indeed show a clear and statistically significant negative gradient in both variables.

The definition of the centre based on maximal shop density may look somewhat arbitrary, while the way the center of a shopping area is defined is crucial for interpretation of our further results. To ensure robustness, we will also use two alternative definitions: (i) the geographical centroid, and (ii) the spot with the highest footfall. The distances from shops in our data to the center of the corresponding shopping area, computed using the three discussed definitions of the center, show a high correlation of 0.85.

2.2 Analytical framework to analyze competition between residential and retail land use

In this section, we build upon the stylized facts presented in Section 2.1. We suggest an analytical framework that models competition between retail and residential land uses in a city.

Consider a two-dimensional city in which land is equally suitable for residential and retail use. A city contains shopping areas $s \in S$, of which the number and the geographical centres C_s are given exogenously. Every shopping area *s* is symmetric around C_s and characterized by a retail bid-rent curve $R_s(r)$ where *r* is the distance to the shopping area centre C_s. Every location *L* in the city faces (i) a vector of retail bid-rents $R_s(r_{Ls})$ where r_{Ls} is the distance between L and C_s, $s \in S$, and (ii) an exogenously given residential rent $R_h(L)$. Land is owned by absentee landlords, and is assigned to the highest bidder.

We build on three following premises:

(P1) Footfall in a shopping area is a negative function of the distance to the centre of a shopping area (compare Figure 3a). The footfall-distance curve shifts up respectively down as the total number of visitors to the shopping area increases respectively decreases. In Appendix A we formally show that P1 follows from fairly general assumptions about pedestrian behaviour of visitors in the shopping areas.

(P2) The retail profits are a monotonic function of footfall, and the retail bid-rent is a monotonic function of profits. Consequently, the bid-rent curve for retail space has a negative distance decay too (compare Figure 3b) implying $R'_s(r)<0$. Further, the bid-rent curve shifts up respectively down as the total number of visitors to the shopping area increases respectively decreases.

(P3) The residential bid-rent is constant in and around shopping area *s*: $R_{hs}(L) = R_{hs}$.[12]

Figure 4 shows the retail and the residential bid-rent curves in and around shopping area *s* in the city. The layout of the figure is similar to Figure 3b, where the distance to the center of the shopping area is depicted on the x-axis, and the rent on the y-axis. The origin of the figure is the center of the shopping area C_s.

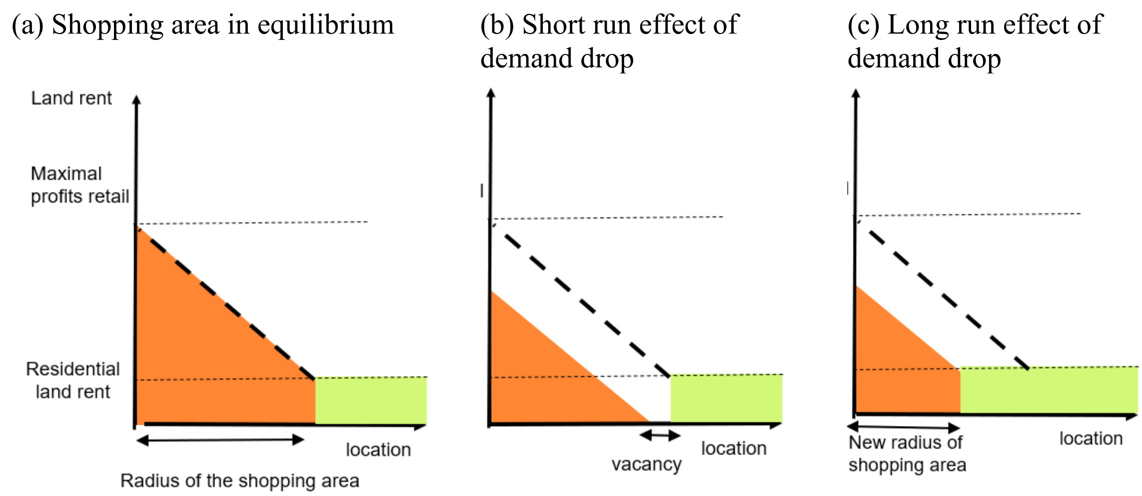
Panel (a) of Figure 4 illustrates a shopping area which is in equilibrium. In C_s, the retail bid-rent is higher than the bid-rent of the competing, residential land use, and the land is optimally allocated to retail.

[12] This assumption is easily generalizable, our results will hold as long as the residential rent gradient is (much) flatter than the retail land gradient. We will show empirically that this is the case.

Retail bid-rent falls with the distance from C_s. At a certain distance $r_s{}^*$ retail bid-rent becomes equal to the residential bid-rent: $R_s(r_s{}^*) = R_{hs}$. This distance $r_s{}^*$ determines the optimal size of shopping area s: beyond $r = r_s{}^*$ land is assigned to competing residential use. Note that in line with premise (P2), the optimal size of a shopping area is the larger the higher the number of visitors to the shopping area (consumer demand) and the lower the bid-rent of the competing residential land use R_{hs}.

Panels (b) and (c) describe the consequences of a negative shock to consumer demand that leads to a drop in the number of visitors to a shopping area. Such shocks have occurred repeatedly in the recent past: the Covid, the arrival of online shopping, the Great Recession following the Financial Crisis of 2008. When the number of visitors decreases, the retail bid-rent curve shifts down (premise P2), making land at the edge more profitable for residential than retail land use.[13] This requires re-assignment of land to another use. However, in the short run, such land transformation to another function may not always feasible, for instance due to zoning restrictions and/or fixed transformation costs. Therefore, in practice, a shopping area at a certain moment in time may be larger than its optimal size, implying that the land rent experiences a discontinuous upwards jump at the edge. If, furthermore, the retail bid-rent has become lower than zero at the edge, vacancy will arise. This is illustrated in Figure 4 panel (b). Here the footfall at the edge of a shopping area is not sufficient to make these locations profitable even at a zero rent. In the longer run this vacant space is likely to be taken over by other land uses which can exploit the land profitably. This is illustrated in Figure 4 panel (c), here residential land use takes over. Similar mechanisms work of an increasing consumer demand, but then in an opposite direction.

Figure 4: Competition between retail and residential land use



Based on this analytical framework we will formulate three hypotheses, to be tested empirically in later Sections.

[13] The opposite occurs following a positive shock to consumer demand.

Hypothesis 1. Within shopping areas, footfall and retail rents command a strong distance decay, while residential rents do not.

The mechanisms behind a distance decay in footfall and retail bid-rent are discussed above and in Appendix A. Concerning the residential bid-rent in and around the shopping areas, one might expect a negative gradient especially in downtowns, due to the well-known monocentric city pattern. However, as this pattern is currently driven by rapid transportation modes as a car or a metro, it will likely manifest itself on much larger distances than the 500x500 meter area a median shopping area in our data covers. (See e.g. Combes et al., 2018 who studies housing prices gradients for the French cities). Therefore we expect a much flatter distance decay in residential as compared to retail rents.

Hypothesis 2. *Vacancies and non-retail (mixed) land use concentrate at the edges of shopping areas.*

The clustering of vacancies at the edge follows from the above model, see Figure 4b. To derive the hypothesis about mixed land use, we need to extend the model. Liu et al. (2018) argues that, in multistorey buildings, retail mainly occupies the ground floors, because of the reluctance of visitors to go to higher floors. In this setting, one would expect some non-retail land use already in the centre of the shopping area, increasing towards the edges and finally fully taking over from retail.

Hypothesis 3. *A negative shock to consumer 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 land use, more so at the edges of shopping areas.*

The fall in rents after a negative shock in demand follows from P2, while a rise in vacancies is in line with Figure 4b. Transformations in the long run are as described in Figure 4c.

3 Empirical specification and data

3.1 Empirical model and identification

We aim to offer empirical support to the three hypotheses above, using data on rents, vacancies and transformations in the Dutch shopping areas in the period 2004-2018, including the aftermath of the Great Recession. Table 2 reports the empirical specifications that will be estimated.

Table 2: Equations to estimate

		dependent	independent
1a	OLS Footfall	lnF_{ist}	X_{is}, d_{is}, I_s, T
1b	OLS Retail rents	lnR_{ist}	X_{ist}, d_{ist}, I_s, T
1c	OLS Residential prices	lnP_{ist}	X_{ist}, d_{ist}, I_s, T
2a	Logit vacant shop	$Pr_{is}[vacant\ shop]$	$X_{is}, d_{is}^{rel}, I_s$
2b	Logit non-retail land use	$Pr_{is}[non-retail]$	$X_{is}, d_{is}^{rel}, I_s$
3	Logit transformation retail to other use	$Pr_{ist}[transformed]$	$X_{ist}, d_{ist}^{rel}, I_s$

Specifications 1a-1c test Hypothesis 1 by estimating the gradients for the footfall (F), retail rents *(R)* and residential prices (P), for property i 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 (X), shopping area fixed effects and characteristics (I), and a time trend (T).

We are mainly interested in the distance gradient – the coefficient by the variable *d*. We will allow for heterogeneity of the coefficient: by type of shopping area (downtown retail, non-central shopping districts, shopping streets) and by the available facilities (free parking, cultural amenities).

Specifications 2a and 2b use logit models to test Hypothesis 2 that vacancy and non-retail land use cluster at the edge of shopping areas. Because the shopping areas differ by size, we need an unambiguous definition of the edge. For this purpose, we transform the geographical distance to the center into a relative distance measured on a scale 0 to 1, where 0 corresponds to the center and 1 corresponds to the edge: $d_{Ls}^{rel} = d_{Ls}/\ max_l(d_{ls})$, $d_{is}^{rel} \in [0, 1]$. Other explanatory variables in these specifications are identical to those used in specification 1.

Finally, specification 3 aims to provide support to Hypothesis 3 about transformations from retail to other use being clustered at the edges of shopping areas. We use a time span 2010-2016 following the Great Recession of late 2000, in which retail vacancy in the Netherlands increased with 1.5 times. We estimate the probability that a property that was a shop at the start of this study period, was transformed to another use by the end of it. The explanatory variables are the same as in Specifications 1 and 2.

All specifications are run with shopping area fixed effects, and the errors are also clustered at the shopping area level. Specifications (1a)-(1c) include twoway fixed effects (shopping area and time).

We will provide a number of robustness checks. First, we will run the models using the three alternative definitions of the centre of a shopping area, as discussed in Section 2.1. Further, different datasets will be exploited.

3.2 Data

In the empirical analysis we exploit a combination of five unique datasets. These are described below one by one. Datasets 1 – 4 include property-level data of which geolocation (address) is known. This to merge the data and also to calculate for each property the distance to the centre of the corresponding shopping area.

3.2.1 Universe of real estate properties in the Netherlands

The Dutch dataset BAG (Basisregistraties Adressen en Gebouwen – Key Register of Addresses and Buildings), provides data on the full universe of real estate properties in the Netherlands. This dataset is publicly available from the Netherlands' Cadastre and Public Register Agency (Kadaster). For all real estate properties it yields information about floor space, geolocation, construction year and the use function (including living, business, retail, etc.), on a yearly basis. We use BAG-data 2010-2016. The BAG data are used for models (2b) and (3), see Table 2.

3.2.2 Universe of retail properties in the Netherlands

For the retail properties, additional data are available from Locatus (2014), including: whether the shop is vacant in the year of observation; whether a shop is part of a mall.[14] Further, for a subsample of shopping areas, the footfall (number of visitors in front of each shop on a Saturday outside holiday periods) is known. These data are used for models (1a), (2a) in Table 2 and to calculate alternative definitions of the centres of the shopping areas.

3.2.3 Two samples with retail rent transactions

We exploit two datasets with information on new rent contracts for retail properties. Both datasets are longitudinal and include for each property: floor space, rents per m^2, year in which the contract was signed.[15] The two datasets differ in terms of the time period they cover and the source of information on rents. The first dataset 2004-2017 is provided by the Dutch real estate advisory company Strabo and contains contracts, for which information was made publicly available through internet or newspapers. The second dataset 2009-2014 has been provided by the international real estate service provider Jones Lang Lasalle (JLL). It includes the Strabo-observations for the years in question, expanded with non-publicly available rent contracts of JLL clients. These data are used in model 1b (Table 2).

3.2.4 Residential sale transactions

Finally, data on residential sale transactions of apartments within the shopping areas of our interest are provided by NVM the Netherlands Association of Real Estate Brokers and Property Experts. The data include the transaction price and structural characteristics of the dwellings, for the years 2009-2018. As residential properties in shopping areas are mostly apartments, we restrict the data to apartments only. The residential sale data are used in model 1c (Table 2).

3.2.5 Data on the shopping area characteristics

For each shopping area we have collected information about its type and the facilities available, in order to be able to study the heterogeneity in the retail land use. We know the type of shopping area: downtown, noncentral, shopping street (source Locatus); parking tariffs (source Ministry of Transport); cultural facilities as approximated by the density of monuments in a shopping area (source Dutch Monuments Register).

[14] Malls are defined as *parts of the shopping areas* that have been developed according to a single plan of the same architect. These may be indoor or outdoor malls. They often have a single owner or manager. We expect that retail properties in malls have ceteris paribus higher rent levels and a higher footfall because a single manager can internalize the externalities shops exert on one another (Gould et al., 2005).

[15] It is also known whether the property was newly built or renovated when the rental transaction took place. We drop newly built or renovated properties because they consider a small share of the data (less than 1%).

Table 3: Descriptive statistics data samples

	Universe of all properties[a]	Universe of shops[b]	Shops JLL[c]	Rent contracts Strabo[d]	Apartment sale contracts[e]
Outcome variables					
Retail rent (1000 euro/m2/year)			0.3	0.27	
			(0.26)	(0.2)	
Residential price (1000 euro/m2)					2.5
					(0.91)
Retail property 1/0	0.2				
Residential property 1/0	0.66				
Footfall (x1000 visitors)		12.15	11.87	10.88	
		(10.58)	(11.73)	(10.16)	
Vacant shop 1/0		0.11			
Other property characteristics					
Distance to centre shopping area (x100m)	2.92	2.09	2.27	2.11	2.88
	(2.6)	(1.98)	(1.87)	(1.75)	(2.36)
Floor space in m2	157.22	191.78	196.18	217.97	85.17
	(337.44)	(429.36)	(275.68)	(271.48)	(28.61)
Constr.yr. < 1945	0.49	0.46	0.49	0.47	0.3
Constr.yr. > 2000	0.11	0.08	0.07	0.07	0.2
Part of a mall 1/0	0.1	0.23	0.17	0.18	0.11
Located in shopping street 1/0	0.15	0.1	0.1	0.08	0.19
Located in non-central shopping district 1/0	0.03	0.05	0.03	0.05	0.03
# monuments in 1km (x1000)	0.37	0.27	0.33	0.25	0.26
	(0.82)	(0.66)	(0.64)	(0.48)	(0.64)
Free parking 1/0	0.2	0.24	0.16	0.2	0.18
# shops in 250m	24.69	29.85	32.79	33.24	23.75
	(13.69)	(15.66)	(17.14)	(17.55)	(12.47)
# properties	240016	46162	3685	5836	19367
# shopping areas	327	327	327	383	303

Notes: (a) Source BAG 2014; (b) Source Locatus 2014; (c) Source JLL 2009-2014; (d) Source Strabo 2004-2017; (e) Source NVM 2009-2018; (f) Footfall in available for 121 shopping areas. The table reports the means and in parentheses the standard deviations.

3.2.6 Data descriptives

We merge the datasets on geolocation and exact address. Table 3 reports the descriptive statistics of the resulting data. Note that shopping areas in our data are quite large and house on average 730 properties of which only 20% is retail. The intuition for this mix of land uses is simple. First, small retailers often live above their shops. Second, many of our shopping areas are located in cities where multistorey buildings are common. Liu et al. (2018) show that retail is predominantly concentrated on the ground floors (plints) of multistorey buildings and leaves other floors to other uses.

An average shop in our data has 200m2 space, which is 1.5 times larger than the average apartment of 80m2. Properties in the shopping areas have some 25 other properties in the 250 meter proximity and are located on a distance of some 300 meter from the centre of the area; shops are on average clustered more near the centre than other types of real estate. Finally, 15% properties in our data is located in shopping streets and 3% in non-central shopping districts. An average shop faces a 10% probability to be vacant.

4 Estimation results

4.1 Distance decay in shopping areas (hypothesis 1)

Table 4 reports the estimation results for the gradients in the footfall, retail rents and residential prices (specifications 1a-1c from Table 2). We use shopping area fixed effects and clustered standard errors. We include various regressors to account for observed heterogeneity between properties. We account for the heterogeneity between shopping areas by including cross-effects of distance with shopping area characteristics.

Let us first consider the results for the footfall and the retail rent gradients. In line with hypothesis 1, both, footfall and retail rents command a negative and highly statistically significant distance decay (see columns 1a and 1b in Table 4). The gradient is flatter in areas with many cultural amenities, and, for the rents, also in park-free areas and shopping streets. The decay for non-central shopping districts does not show statistically significant differences with the main coefficient. Estimated coefficients by the structural and locational characteristics are in line with the intuition. Larger shops command lower rent by m^2 floor space but a higher footfall; properties located within malls have higher rents and higher footfall.

Let us now look at the residential price gradient (model 1c in Table 4). While we do find a negative and statistically significant coefficient, its size is almost 20 times smaller than of the retail rent gradient. The monocentric city pattern, in line with the hypothesis 2, obviously manifests itself on much larger distances than the 500x500 meter area a median shopping area in our data covers.

We subject the results from Table 4 to various robustness checks, see Appendix B. First, one might be worried that the floor space is endogenous in models (1a) and (1b), for example if larger shops choose to sit in most popular spots. To test this, we run the same two regressions without the floor space covariate and obtain practically the same values for the distance coefficient (Table B1). Further, we show robustness to different definitions of the centre (Table B2 and B3), an alternative dataset with retail rents (Table B4) and to a more flexible second order polynomial function of distance (Table B5).

Table 4: Distance gradients in shopping areas

	Footfall (log) (1a)	Retail rents (log) (1b)	Residential prices (log) (1c)
Distance (x100m)	-0.383***	-0.230***	-0.015**
	(0.06)	(0.03)	(0.01)
Distance x Shopping street[(a)]		0.106***	0.010***
		(0.03)	(0.00)
Distance x Non-central shopping area	-0.074	0.083	0.008
	(0.14)	(0.07)	(0.02)
Distance x (log)Monuments	0.039***	0.020***	0.002**
	(0.01)	(0.00)	(0.00)
Distance x Park-free	-0.073	0.128***	0.009
	(0.08)	(0.03)	(0.01)
(log) Floor space	0.093***	-0.302***	-0.274***
	(0.01)	(0.01)	(0.01)
Located in a mall 1/0	0.165**	0.307***	-0.004
	(0.07)	(0.04)	(0.01)
Lift 1/0			0.028***
			(0.00)
Own parking space 1/0			0.099***
			(0.01)
Nice view 1/0			0.046***
			(0.00)
Bad maintenance outside 1/0			-0.085***
			(0.01)
Bad maintenance inside 1/0			-0.127***
			(0.01)
Constr.period fixed effects	YES	YES	YES
Transaction year fixed effects	NO	YES	YES
Transaction month fixed effects	NO	NO	YES
Shopping area fixed effects	121	327	303
Observations	23,509	3,685	19,367
R^2	0.137	0.300	0.438

Notes: *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are in parentheses. Standard errors are clustered by shopping area.
[(a)]There are few observations for footfall in streets, so no coefficient for footfall could be estimated.

To get a better insight into the heterogeneity of the retail rent gradients by shopping area type, Table 5 calculates the gradients for a number of example shopping areas from our data (kolom 1b). In line with the estimation results, the gradients are flatter for shopping areas with better amenities and facilities. For instance, the retail rent gradient is −23% in a shopping area with paid parking and few (10^{th} centile) monuments. The gradient becomes flatter with the rising number of monuments (−16% at the 90^{th} centile), and much flatter once parking is free (−7%). A flatter distance decay in rents suggests, *ceteris paribus*, a larger shopping area (see Figure 4). Although, based on our model no conclusions about causal effects can be made, the results present suggestive evidence that shopping areas with better amenities and facilities *ceteris paribus* will command a larger size. In line with this insight, investing in facilities may be a possible way for shopping areas to tackle vacancies that arise following drops in consumer demand. The economic intuition is that facilities (e.g. free parking) will motivate visitors to stay longer. In this way, a drop in the total number of visitors can be compensated by the length of the stay: a single visitor will then pass by more shops.

Table 5: Distance gradient by type of shopping area

	Footfall	Retail rent	Residential rent
Average shopping area	-0.260	-0.191	-0.001
Street, no free parking, median monuments[(a)]		-0.070	0.000
No street, free parking, median monuments	-0.066	-0.075	-0.004
No street, no free parking, 90 percentile monuments	-0.118	-0.159	-0.003
No street, no free parking, 10 percentile monuments	-0.396	-0.226	0.000

Notes: The figures in the table indicate the relative decrease in the footfall, residential and retail rent respectively with each additional 100 meter from the centre of a shopping area.
[(a)]There are few observations for footfall in streets, so no coefficient for footfall could have been estimated.

4.2 Vacancy and non-retail clustering at the edge (hypothesis 2)

To test Hypothesis 2, we use the complete universe of the properties - retail and non-retail - in the shopping areas of our sample. We use two samples: shopping areas with known rents (these are the same 327 areas as used in the retail rent gradient estimation) and the full sample of larger shopping areas (446 areas, see Section 2). Table 6 reports the results. Both datasets yield consistent estimates and all the coefficients are in line with the theoretical predictions. The distance coefficient is positive and highly statistically significant for both, vacancy and non-retail use. This means that closer to the edge of a shopping area, retail vacancy increases and land use gets more mixed. The odds ratio between the edge and the center equals 2 for vacancy and 8 for non-retail use. Shopping streets command lower odds ratios. Areas with free parking have a lower odds ratio for the vacancy and areas with many cultural amenities have a lower odds ratio for non-retail use. These results support the model of Section 3 and are in line with the findings of the previous Section for the rent gradients.

4.3 Dutch retail during the Great Recession (hypothesis 3)

Finally , below we provide some evidence in support of Hypothesis 3. In the aftermath of the Great Recession, 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% during 2008-2014. Our analytical 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 uses, more so at the edges of the shopping areas.

Table 6: Logit distance effect vacancy and non-retail use

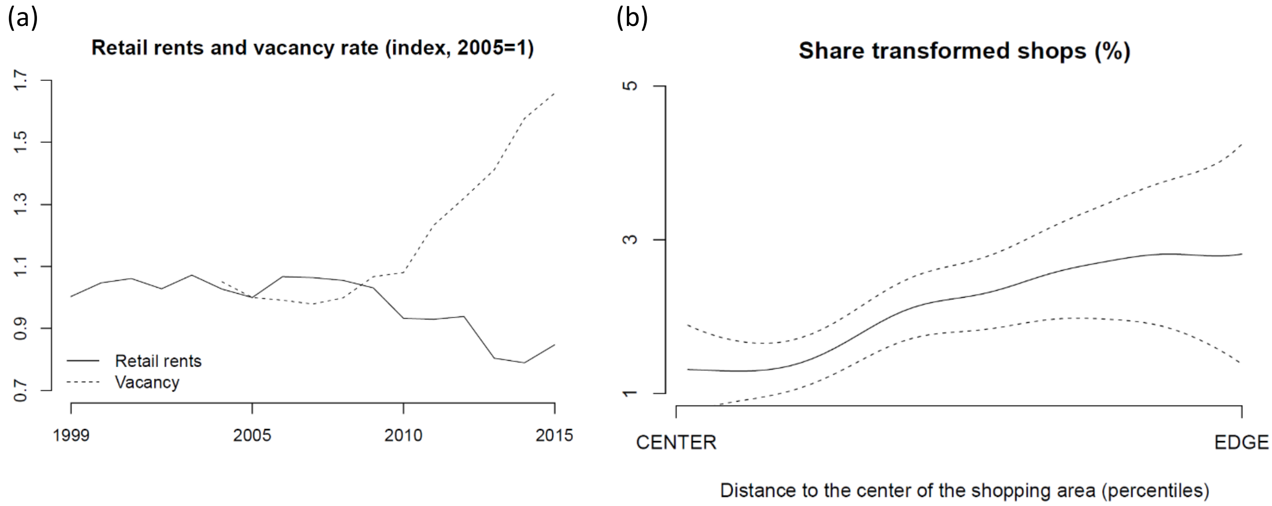
	Larger shopping areas known rents		All larger shopping areas	
	Vacancy	Non-retail use	Vacancy	Non-retail use
	(2a)	(2b)	(2a)	(2b)
Centile distance (/10)	0.840***	2.727***	1.170***	2.598***
	(0.29)	(0.35)	(0.25)	(0.32)
Centile distance x Shopping street	-0.556*	-1.307***	-0.708***	-1.347***
	(0.29)	(0.23)	(0.24)	(0.20)
Centile distance x Non-central shopping area	-0.011	-0.089	-0.244	0.115
	(0.54)	(0.60)	(0.35)	(0.51)
Centile distance x (log)Monuments	0.001	-0.179**	0.033	-0.151**
	(0.06)	(0.08)	(0.06)	(0.08)
Centile distance x Park-free	-0.543**	0.171	-0.606***	0.156
	(0.25)	(0.18)	(0.19)	(0.16)
(log) Floor space	0.049***	-0.764***	0.039***	-0.761***
	(0.02)	(0.03)	(0.01)	(0.03)
Located in a mall 1/0	0.062	-1.197***	-0.319***	-1.188***
	(0.07)	(0.09)	(0.08)	(0.09)
Constr.period fixed effects	YES	YES	YES	YES
Shopping area fixed effects	YES	YES	YES	YES
Shopping area clusters	327	327	446	446
Observations	46,162	240,016	55,792	271,859

Notes:Standard errors are in parentheses. *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are clustered by shopping area.

We run an OLS of the rents and a logit of the vacancy (specifications 1b and 2a in Table 2) again, for the years 2004-2014. Figure 5a shows the year fixed effects. The behavior of the rents and vacancies is in line with the predictions of the analytical model. Before 2008 (the first year of the Great Recession) neither the rents nor the vacancy levels changed much. Between 2008 and 2014 rents fell by 20%, and simultaneously, vacancies rose by a factor 1.6.

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. For all properties in our shopping areas we have data on their recorded function in these years, from the dataset on the universe of Dutch real estate properties BAG. It turns out however that the data contain noise. A change in the recorded function of a property does not always reflect a transformation, but can also be consequence of an administrative correction of an erroneous initial data record. To correct for this noise, we approached all the municipalities in which the shopping areas of our sample are located with a request to check the potentially transformed properties obtained from BAG. 26 municipalities housing 49 shopping areas agreed to help in distinguishing real transformations from administrative corrections. The resulting sample includes all retail properties in these shopping areas, which make 25% of our main sample.

Figure 5: Retail rents, vacancies and transformations during Great Recession



Notes: Panel (a) depicts year fixed effects from two specifications: an hedonic OLS of retail rents and a logit of vacancy. The values of fixed effects have been transformed to an index with 2005 as 1. Panel (b) reports a non-parametric estimate of the percentage properties transformed from retail to residential function, as a function of the distance to the center of the shopping area.

In these data, some 2% of the properties that had been retail in 2010, was transformed in the following 6 years. Figure 5b reports a non-parametric estimate of the probability of a shop being transformed to residential use, as a function of the distance from the center of a shopping area. In line with the predictions of the analytical model, most transformations took place at the edges of the shopping areas. Table 7 reports the results from a formal logit model explaining the probability that a retail property was transformed to another use, from the structural characteristics of the shop and its location. The distance effect is positive and statistically significant. The odds ratio between edge and center equals 3.5.

Table 7: Logit distance effect transformation probability

	Transformation 1/0
Centile distance (/10)	1.237***
	(3.41)
(log) Floor space	-0.176**
	(-2.18)
Located in a mall 1/0	-1.555**
	(-2.39)
Construction period fixed effects	YES
Shopping area fixed effects	49
Observations	8,650

Notes:We cluster standard errors at the neighbourhood level. Standard errors are in parentheses. *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are clustered by shopping area.

5 Policy implications

For more than a decade now, brick-and-mortar stores are melting down in various countries, and vacancies are an eyesore and a source of negative externalities. Up to recently, the classic hog cycle pattern governed the development of vacancy rates in retail real estate.[16] Excessive supply of new floor space and corresponding high vacancies could be tackled by stopping new construction and waiting for the growing retail space demand to push the vacancy rate back again. The necessary condition of growing retail demand seems however not to hold in the long run any more, not in the last place due to the constantly increasing share of online retail. For example, the economic recovery from the Great Recession that started in the Netherlands in 2015, did not lead to a recovery in retail demand in the years after,[17] and the retail vacancy stayed high until another consumption shock, due to the Covid, happened in 2020.

Our research suggests that transformations at the edges of shopping areas may be a new regulatory mechanism that can govern the excess retail vacancy when the hog cycle does not work any more. In a situation when a drop in physical retail demand might be permanent, some locations at the edges of the shopping areas become unprofitable for retail at any level of rent. In a longer run these locations will loose their retail function and be taken over by competing land uses. This seems to be happening in the Netherlands: the modest decrease in vacancy rate in 2018 was fully attributed to transformations from retail to other use (Rabobank, 2019).

A necessary condition for a transformation is that a location is more profitable for other land use than for retail (see Figure 4c). Transformations are thus most likely to happen in places where demand for retail land has dropped, but demand for land for competing uses stays high. This holds for instance for edges of downtowns in larger cities. In areas where the overall demand for land is declining, for instance due to the declining population, the transformation potential will likely be much lower. There some kind of governmental intervention might be needed to resolve the structural vacancy.

6 Conclusion

We developed and estimated a novel model that describes the spatial structure of urban shopping areas and analyses competition between retail and residential land in a city. Empirical support for the model is based on property-level data from almost fifty thousand shops located in 327 Dutch shopping areas, including downtown retail, non-central shopping districts and shopping streets. The main driving force behind the results is the finding that shopping areas command a strong negative retail rent gradient from the centre to the edges, averaging to −20% per 100 meter distance. This retail rent gradient is ten to twenty times stronger than the residential rent gradient estimated in the same shopping areas. Using this finding, we argue that the competition between retail and residential land determines the size of the shopping areas and also helps tackle negative consequences of a drop in consumer demand for brick-and-mortar retail.

[16] Dynamics known as the "hog cycle", describes a situation when demand responds to current prices but supply responds to previous year prices. As a result, prices can cycle up and down because supply is first inadequate and then excessive.

[17] On the contrary, demand has been falling further. E.g. in 2018 15% less new floor space was rented than in 2017. (Rabobank, 2018)

The land market perspective on the developments in the retail real estate yields useful practical insights. The demand for brick-and-mortar stores has been continuously falling during the last decade. Our study suggests that the resulting structural vacancies mostly cluster at the edges of the shopping areas, since a negative demand shock most heavily affects retail at those locations. The vacancy clustering at the edges is good news. In regions and cities with high enough demand for land, these vacant spots will be gradually taken over by other adjacent land uses, leading to a natural contraction of shopping areas and elimination of the vacancies. However, in declining cities and regions, transformation of land to other use is less likely to occur through market forces. To tackle structural retail vacancy there, public policy measures may be needed.

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Online Appendix A. Pedestrian behavior and a negative footfall gradient in shopping areas

We model a shopping area as a network of interconnected walkable nodes – we call these 'combs' – which host shops.[18] Our model rests on the following assumptions:

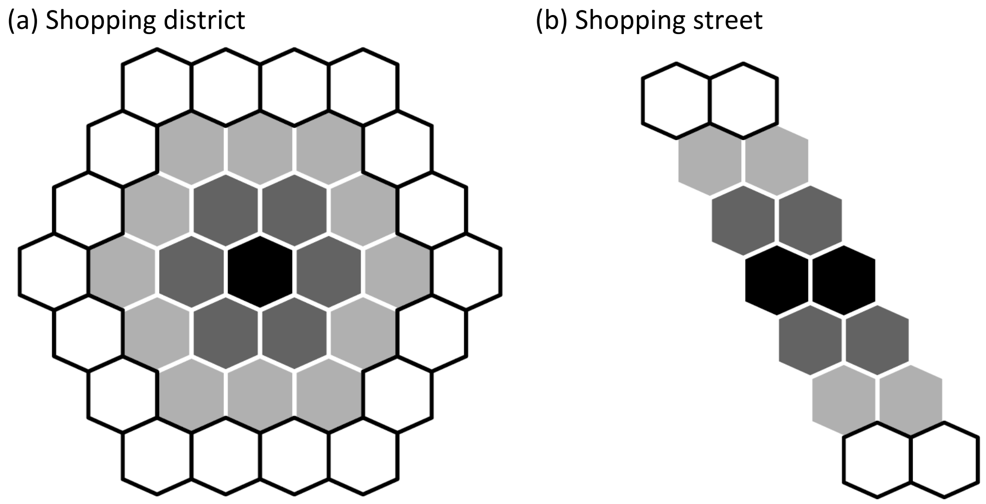
(i) There are two possible structures of the shopping area: a shopping district (Figure A1a), where nodes are located in symmetric consecutive rings, and a shopping street (Figure A1b), where nodes are located in two parallel lines that represent two sides of a shopping street. Nodes host shops, all adjacent nodes are connected by walkable links.

(ii) Nodes are assigned to rings $r \in [0..\bar{r}]$, where r is the distance (minimal number of links) needed to reach the geographic centre of the shopping area, and $\bar{r}$ is called the radius of the shopping area.

(iii) A consumer visiting a shopping area starts her shopping trip in a randomly assigned node. Then she moves in a random walk through the area. In each step she has a probability p_r to leave the area, such that: $p_r = p_0$ if $r < \bar{r}$ and $p_r = p_E$ if $r = \bar{r}$. We assume $p_E > p_0$, because by construction nodes on the edge of the shopping area have fewer links.

(iv) Let $Pr(r|\bar{r}, p_0, p_E, k) > 0$ be the probability that a consumer ends up in a node belonging to ring r on step k in her trip. Let N be the total number of visitors to the shopping area.

Figure A1: Honeycomb structure of the shopping areas



Notes: We model shopping areas as honeycombs or networks of combs hosting shops. By assumption, the combs are connected by links to adjacent combs. The center of a shopping area is determined exogenously. The distance from a comb to the center r∈[0..r⌉ is defined as the minimal number of steps needed to reach the center from a comb. We call the set of combs which share the same distance *r*, ring r. The edge combs are defined by r=max(r). Note that this Figure gives a top view of the shopping areas.

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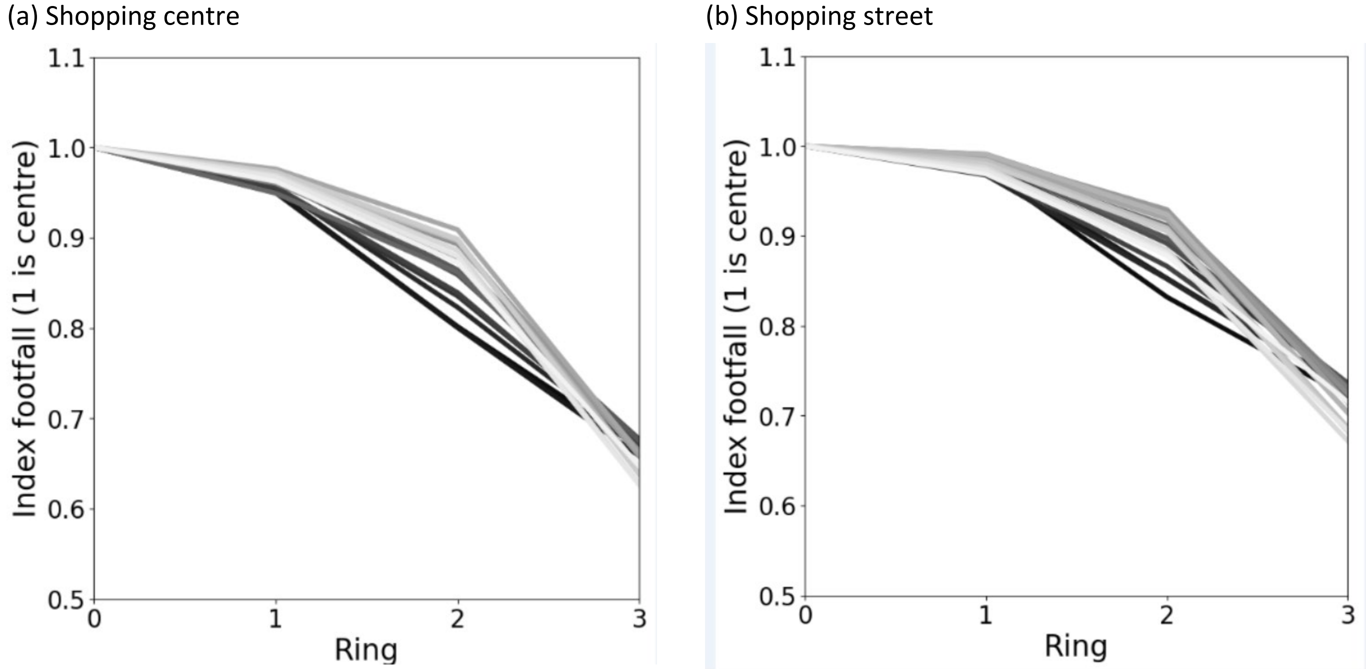
[18] A somewhat similar representation of a shopping area as a network of walkable sections connected to each other at cross-streets is used in simulation studies of pedestrian walking behavior (see e.g. Borgers and Timmermans, 1986, and the studies that followed). Antonini et al. (2016) and Robin et al. (2009) discuss other pedestrian walking behaviour models.

From (i)-(iv), we can derive the expected number of times a single consumer visits ring r during her trip: $v(r) = \sum_{k=1}^{\infty} Pr(r|\bar{r}, p_0, p_E, k)$. Then the expected footfall in a node of ring *r*, can be written down as: $Nv(r)$. Below we simulate $Nv(r)$ numerically for $\bar{r} = 3$ and show that, for a variety of p_0, p_E, $Nv(r)$ monotonically decreases in *r*.

By definition, the shopping trips of the consumers are Markov chains with uniform transition probabilities across all neighboring combs. For given values of $\bar{r}$, p_0, , p_E we can easily compute $v(r)$ through simulation.[19] Note that for a value of K sufficiently large $\lim_{k \to K} Pr(r|\bar{r}, p_0, p_E, k) = 0$, so it is sufficient to compute $v(r)$ for a finite number of steps. We run the simulation 300.000 times with *K*=100 and $\mathrm{p_E} \in [0.05, 0.1, .., 0.9, 0.95]$ and $p_0 = 0.5p_E$. Figure A2 reports the resulting distance decay in the number of visitors as an index, which takes value 1 in *r* = 0. Note that while Figure A1 presented a top view of a shopping area, Figure A2 gives a side view.

Figure A2: Distance decay in footfall for shopping areas with r=3



Notes: The Figure reports simulated values of $\mathrm{E[v(r)]} = \sum_{k=1}^{\infty} \mathrm{Pr(r|\bar{r}, p_0, p_E, k)}$, the expected number of times a single consumer visits a comb located in ring r. E[v(r)] is computed as an average over all combs belonging to ring r and expressed as an index with the central ring taking the value 1. We run the simulation for N=300.000 visitors, each of whom makes at most K=100 steps during the trip. The Figure reports 20 simulations for $\mathrm{p_E} \in [0.05, 0.1, .., 0.9, 0.95]$ and $\mathrm{p_0} = 0.5\mathrm{p_E}$. Lines become darker with a higher value of $\mathrm{p_E}$.

The simulation yields a negative distance decay in the probability to visit a node in ring *r*. The footfall in each node depends on this probability multiplied with the total number of visitors that arrive to the shopping area within a unit of time (consumer demand). Consequently, increases respectively decreases in the consumer demand will shift the footfall curve upwards respectively downwards.

[19] To compute $E[v(r)]$, an average over all combs belonging to ring *r* is taken.

The distance decay in Figure A2 follows from fairly general assumptions about the walking behavior of visitors in a shopping area. In reality, people usually do not arrive to the shopping area at random places. There are reasons why a relatively large share of visitors starts their shopping trip in a more central location. For example, because transit hubs (bus stop /metro station/ parking garage) are located there, but also due to a higher density of shops (see stylized facts of Section 2). Obviously, more centrally clustered arrivals will only enforce the negative distance decay.

Online Appendix B. Robustness checks

Table B1: Gradients footfall, retail rents, residential prices: floor space removed as covariate

	Footfall (log) (1a)	Retail rents (log) (1b)	Residential prices (log) (1c)
Distance (x100m)	-0.378***	-0.245***	-0.014**
	(0.06)	(0.03)	(0.01)
Distance x Shopping street		0.113***	0.005*
		(0.03)	(0.00)
Distance x Non-central shopping area	-0.058	0.124	0.002
	(0.14)	(0.12)	(0.02)
Distance x (log)Monuments	0.038***	0.024***	0.002**
	(0.01)	(0.00)	(0.00)
Distance x Park-free	-0.074	0.101***	0.009
	(0.08)	(0.03)	(0.01)
Constr.period fixed effects	YES	YES	YES
Transaction year fixed effects	NO	YES	YES
Transaction month fixed effects	NO	NO	YES
Shopping area fixed effects	121	327	303
Observations	23,509	3,685	19,367
R^2	0.123	0.150	0.318

Notes: *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are in parentheses. Standard errors are clustered by shopping area. The table only reports distance coefficients, other coefficients are available upon request..

Table B2: Gradient footfall, retail rents, residential prices: centre as geographical centroid

	Visitors (log)	Retail rents (log)	Residential prices (log)
	(1)	(2)	(3)
Distance (x100m)	-0.477***	-0.245***	-0.017**
	(0.06)	(0.03)	(0.01)
Distance x Shopping street	0.128***	0.140***	0.011***
	(0.02)	(0.03)	(0.00)
Distance x Non-central shopping area	-0.308**	0.047	0.034***
	(0.15)	(0.07)	(0.01)
Distance x (log)Monuments	0.045***	0.018***	0.002*
	(0.01)	(0.01)	(0.00)
Distance x Park-free	-0.168**	0.096***	0.011
	(0.07)	(0.03)	(0.01)
Constr.period fixed effects	YES	YES	YES
Transaction year fixed effects	NO	YES	YES
Transaction month fixed effects	NO	NO	YES
Shopping area fixed effects	121	327	303
Observations	23,509	3,685	19,367
R^2	0.173	0.316	0.438

Notes: *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are in parentheses. Standard errors are clustered by shopping area. The table only reports distance coefficients, other coefficients are available upon request.

Table B3: Gradient footfall, retail rents, residential prices; centre based on highest footfall

	Visitors (log)	Retail rents (log)	Residential prices (log)
	(1)	(2)	(3)
Distance (x100m)	-0.430***	-0.216***	-0.011*
	(0.05)	(0.03)	(0.01)
Distance x Shopping street	0.039	0.077***	0.009***
	(0.04)	(0.03)	(0.00)
Distance x Non-central shopping area	-0.129**	0.134	0.021**
	(0.05)	(0.10)	(0.01)
Distance x (log)Monuments	0.036***	0.015***	0.002*
	(0.01)	(0.01)	(0.00)
Distance x Park-free	-0.198***	-0.032	0.031**
	(0.05)	(0.08)	(0.01)
Constr.period fixed effects	YES	YES	YES
Transaction year fixed effects	NO	YES	YES
Transaction month fixed effects	NO	NO	YES
Shopping area fixed effects	121	121	111
Observations	23,509	2,763	12,990
R^2	0.226	0.338	0.452

Notes: *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are in parentheses. Standard errors are clustered by shopping area. The table only reports distance coefficients, other coefficients are available upon request.

Table B4: Gradient footfall, retail rents and residential prices: alternative data (Strabo)

	Visitors (log)	Retail rents (log)	Residential prices (log)
	(1)	(2)	(3)
Distance (x100m)	-0.381***	-0.156***	-0.014**
	(0.06)	(0.03)	(0.01)
Distance x Shopping street	-0.045**	0.082***	0.010***
	(0.02)	(0.02)	(0.00)
Distance x Non-central shopping area	-0.076	-0.058	0.012
	(0.14)	(0.07)	(0.01)
Distance x (log)Monuments	0.039***	0.011**	0.002**
	(0.01)	(0.00)	(0.00)
Distance x Park-free	-0.075	0.048**	0.009
	(0.08)	(0.02)	(0.01)
Constr.period fixed effects	YES	YES	YES
Transaction year fixed effects	NO	YES	YES
Transaction month fixed effects	NO	NO	YES
Shopping area fixed effects	121	383	346
Observations	23,509	5,836	19,922
R^2	0.137	0.352	0.439

Notes: *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are in parentheses. Standard errors are clustered by shopping area. The table only reports distance coefficients, other coefficients are available upon request.

Table B5: Gradient in footfall, retail rents, residential prices: second order polynomial distance

	Visitors (log)	Retail rents (log)	Residential prices (log)
	(1)	(2)	(3)
Distance (x100m)	-0.459***	-0.248***	0.006
	(0.10)	(0.07)	(0.01)
Distance x Shopping street	-0.048	0.121*	0.002
	(0.05)	(0.06)	(0.01)
Distance x Non-central shopping area	0.450*	0.008	-0.047
	(0.26)	(0.13)	(0.04)
Distance x (log)Monuments	0.051**	0.014	-0.001
	(0.02)	(0.01)	(0.00)
Distance x Park-free	0.194	0.117**	-0.003
	(0.17)	(0.06)	(0.02)
Distance squared (x100m)	0.016	0.007	-0.003***
	(0.02)	(0.01)	(0.00)
Distance squared x Shopping street	-0.001	-0.003	0.001**
	(0.01)	(0.01)	(0.00)
Distance squared x Non-central shopping area	-0.111***	0.019	0.013
	(0.04)	(0.02)	(0.01)
Distance squared x (log)Monuments	-0.002	-0.000	0.000***
	(0.00)	(0.00)	(0.00)
Distance squared x Park-free	-0.094***	0.005	0.001
	(0.04)	(0.01)	(0.00)
Constr.period fixed effects	YES	YES	YES
Transaction year fixed effects	NO	YES	YES
Transaction month fixed effects	NO	NO	YES
Shopping area fixed effects	121	327	303
Observations	23,509	3,685	19,367
R^2	0.140	0.305	0.439

Notes: *, **, ***, 10%, 5%, 1% statistical significance, respectively. Standard errors are in parentheses. Standard errors are clustered by shopping area. The table only reports distance coefficients, other coefficients are available upon request.