On shopping externalities: Should we subsidize shops in city centres?*

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SUMMARY — Why do shops agglomerate in city shopping districts? Shops that agglomerate benefit from output sharing: customers reduce their walking distance by visiting clusters of shops. We aim to identify the external effect of retail agglomeration measured by footfall, i.e. the number of pedestrians that pass a shop, on rents of shops, which can be considered as a measure of productivity. We deal with several endogeneity issues by focusing on very local footfall differences between intersecting shopping streets, as local spatial differences in footfall between streets appear to be substantial. On average, the benefit of a pedestrian passing by is about €0.005 per day. The agglomeration elasticity for the retail sector appears to be about ten times higher than the estimates for the non-retail sector. This also suggests that policies that subsidise the concentration of shops can be welfare improving, in particular because we will also test if there is a negative effect of footfall on housing prices. Results using the incidence of becoming vacant for of all shops in the Netherlands confirm that footfall is an important determinant of retail firms' location choices. Finally, we show that increasing the number of shops in a shopping district can stimulate footfall. Given some assumptions, we calculate that the optimal subsidy for a shop to cluster in a dense area is € X.

JEL-code — R30, R33
Keywords — retail, output sharing, agglomeration economies, footfall, hedonic price analysis.

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I. Introduction

Retail markets constitute a large fraction of modern economies, they employ a large part of the population and they facilitate the distribution of final goods and services to consumers. Since the seminal work of Marshall (1890) on agglomeration economies and of Hotelling (1929) on spatial competition, geographers, economists and marketing specialists have attempted to investigate what drives location decisions of retailers[1]. This question is very relevant from a policy perspective too, since land use policies often restrict the availability of land for retail. Policies, such as the 'town-centre-first' policy in UK, *"attempts to concentrate retail development on particular sites on expensive central land and so increases the cost and constrains the quantity of retail space"* (Cheshire et al. 2011). A policy to concentrate retail facilities on certain location may be welfare maximising if output sharing is important. In other words, if external effects of retail concentration are important.

Retail markets differ markedly from other markets in terms of distribution costs. In a retail market, transportation is usually paid for by consumers and the associated transportation costs are incurred on a per shopping trip basis (Claycombe, 1991). Therefore, consumers who visit clusters of shops, shopping districts or shopping malls benefit from increasing returns to scale and scope with respect to consumption and search (Eaton and Lipsey, 1982; Schulz and Stahl, 1996). The associated reductions in transportation and search costs imply an output sharing shopping externality. As a result, shops' productivity functions depend on the extent of output sharing and will reveal these underlying functions through their bidding behaviour for shop locations. The shopping externality is then expected to (fully) capitalise into shop rents, in line with the literature of agglomeration economies (Ahlfeldt et al., 2014; Arzaghi and Henderson, 2008).[2]

Maybe surprisingly, despite the vast amount of theoretical studies on the relationship between agglomeration and retail productivity, we are not aware of any study that analyses the empirical relationship between agglomeration and retail productivity. In the current study, we aim at measuring the causal effect of footfall on retail rents. Footfall is probably the most direct proxy for output sharing, but has, to the best of our knowledge, never been used

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[1] Marshall (1890) defined agglomeration economies as composed by better access to skilled labour (labour market pooling), specialized suppliers (shared inputs), and knowledge spillovers arising when firms are located sufficiently close to each other It should be noted that for the retail industry only input and output sharing seem to be relevant. Most retail establishments do not need highly skilled labour or a large number of workers that labour market pooling can be considered an important source of agglomeration. Knowledge spillovers are also not very relevant since most retail spaces accommodate the activity of sales alone, while management and administration, R&D and the other departments, for which knowledge spillovers are more relevant, are located elsewhere (if they exist at all). For retail, only input and output sharing seem to play an important role.

[2] In retail markets, agglomeration is extremely local, so capitalisation will predominantly occur in rents. In nonretail markets, agglomeration is much less local, so capitalisation occurs not only in rents, but also in wages.

before. We focus on the main Dutch shopping streets, which are mainly located in historical city centres, as is quite common in most European countries. In these shopping streets, customers tend to walk between shops, as parking supply tends to be absent or extremely scarce (Van Ommeren et al., 2014), report 2.5 garage parking spaces per shop).

As is well known in the agglomeration literature, measures of agglomeration tend to be endogenous with respect to rents (because attractive locations will demand higher rents and attract more retail firms). To identify a causal effect of footfall on rents, we exploit variation in footfall of shops that are *very close* to each other (within 50 metres) but on different *intersecting* shopping streets. By focusing on shops that are in such a close proximity, we control for unobservable locational endowments. Because people follow certain routes for their shopping trips, footfall may be substantially different between intersecting streets, which ensures that there is sufficient spatial variation in footfall.

The empirical analysis indicates that footfall has a strong positive effect on retail rents. Our empirical findings imply an elasticity of about 0.2, which is roughly ten times larger than the elasticity found in the agglomeration literature for non-retail firms, where output sharing is a less important phenomenon. This paper contributes to the related theoretical literature by testing several of its predictions. In particular, regarding Konishi's (2005) trade-off between market-size (agglomeration) and price-cutting (competition) effects, we find evidence that agglomeration forces are dominant for the retail sector. Moreover, we confirm the predictions of Smith and Hay (2005) that in shopping streets landowners, rather than retailers internalize the agglomeration effects between products. Our analysis is extended by looking at the vacancy rates. We know whether each shop in the Netherlands is lying empty or not in each specific year. We show that the probability to become vacant is also much lower in areas where footfall is higher, confirming the initial results.

This paper continues as follows. In Section II we outline the econometric framework and discuss identification issues. Section III introduces the data and reports descriptive statistics. In Section IV we present the results, followed by the section V, where we present some counterfactual calculations. Our final conclusions are included in Section V. Finally, Sections A.1 Data appendixA.2. Tables appendix include some additional information about our data and some additional results tables, respectively.

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II. Econometric framework

A. A hedonic price approach

We are interested in the effect of output sharing on rents of retail space. Let p_{ijt} by the log of rental price a retail firm i pays for a property j in year t. Furthermore, let f_{jt} be the daily footfall at each shop location (for more information see the data section), s_{jt} the size of the property and z_{jt} other attributes of the property (e.g. construction year) and location. The basic equation to be estimated yields:

(1) $$p_{ijt} = \alpha f_{jt} + \beta s_{jt} + \gamma z_{jt} + \theta_t + \epsilon_{ijt},$$

where α, β and γ are parameters to be estimated, θ_t are year fixed effects and ϵ_{ijt} is an identically and independently distributed error term.

A well-recognised problem in the above equation is that unobserved attractive features of a location are correlated to the proxy that is used for agglomeration economies (usually density) (Ellison and Glaeser, 1997; Bayer and Timmins, 2007; Combes et al. 2008; Ahlfeldt et al., 2014). This will imply that that footfall f_{jt} and ϵ_{ijt} are correlated. For example, at locations with an attractive retail environment, e.g. nice historic buildings, the density of retail firms is expected to be higher, and so are property values. When one does not account for this omitted variable bias, one is likely to overestimate the importance of agglomeration economies. Furthermore, internal building quality may be important for profits. When internal building quality is non-randomly distributed over space (e.g. nicer buildings in areas with more footfall), and customers value internal building quality this may lead to a bias. Furthermore, due to zoning and other regulations, retail firms may be forced to locate at more expensive locations with more footfall (Cheshire et al., 2015). Different solutions have been proposed to address this kind of endogeneity issues of agglomeration. Many studies use long-lagged instruments or control for proxy, albeit imperfect, for unobserved endowments (Ciccone and Hall, 1996; Melo et al., 2009; Ellison et al., 2010). However, given that we observe extreme persistence of shopping areas over time, it is very plausible that unobserved endowments that were important a century ago are still an important determinant of current rents for shops.

To control for unobserved locational endowments, we include shopping district or shopping street fixed effects. This approach may mitigate the problem of unobserved endowments, but it is unlikely to solve the problem entirely. We therefore also propose another identification strategy, based on the spatial distribution of our output sharing measure. It appears that there are large differences in footfall between intersecting streets because people follow certain routes for their shopping trips.[3] Our idea is to compare shops that are very close to intersections of streets (within 50 metres). Locations close to intersections are arguably identical in unobserved spatial components, such as local policies and general accessibility. Let d_n be the distance to the nearest intersection n in metres. We then estimate:

(2) $$p_{ijt} = \alpha f_{jt} + \beta s_{jt} + \gamma z_{jt} + \eta_n + \theta_t + \epsilon_{ijt}. \quad \text{if } d_{jn} < 50,$$

One may argue that streets may have different widths, which might be important; for example, because smaller streets may imply less visibility. We therefore calculate for each shop the distance to the opposite side of a street, as well as the length of a shopping street and define whether a shop is inside a mall (for more information see the data section). We then include these shopping street characteristics c_j in the regression:

[3] We illustrate this in Figure A1 in the Appendix for a small part of the Amsterdam city centre: close to intersections there are large differences in footfall conditional on the street the shop is located.

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(3) $$p_{ijt} = \alpha f_{jt} + \beta s_{jt} + \gamma z_{jt} + \delta c_j + \eta_n + \theta_t + \epsilon_{ijt}, \quad \text{if } d_{jn} < 50,$$

where δ are additional parameters to be estimated.

B. The effect of footfall on vacancy rates

III. Data and descriptives

A. Data

The data that are used in this paper are based on two unique datasets with information on the retail sector in the Netherlands. The first of these datasets was obtained by *Strabo*, a consultancy firm that gathers and analyses commercial property data. It comprises transactions of commercial properties provided by real estate agents from 1986 to 2015. The dataset contains information about annual rent and rental property attributes, such as address, size (gross floor area in m^2), whether the shop is a sublet and whether the building is newly constructed or renovated. From the Strabo dataset, we exclude vacant shops and a handful of shops with zero or missing rents. After this first selection, the commercial rents dataset is matched to data from the *Administration of Buildings and Addresses*, which provides the exact location and construction year for all buildings in the Netherlands. The matching was based on the nearest neighbour within 5m criterion. Based on the *Listed Building Register*, we have added information on whether the rental property is in an area that is assigned as an historic district. The latter is relevant since about half of all shops are within such a district. The dataset is also merged with detailed land use data from *Statistics Netherlands*. The latter data enable the calculation of distance to the nearest water body and to the nearest train station.

The second dataset is the *Locatus* retail dataset, which contains the *full* population of retail establishments in the Netherlands from 2003 to 2015, as well as counts of footfall in the *main* shopping streets of the Netherlands for the same period. For each shop we know what retail sector is occupying the shop and whether the shop is vacant. The annual footfall data, provided by Locatus, is the average footfall collected on two Saturdays in Spring and Autumn (at four different hours of the day day).[4] Footfall represents the average number of shoppers per day. The footfall data are matched to shop locations by Locatus. We have matched each *Strabo* shop to a shop in the *Locatus* dataset and thus, to the footfall data, based on the closest shop within 5m. If there are no *Locatus* shops with footfall data within 5m of a *Strabo* shop, we exclude the *Strabo* shop observation. Thus, we have restricted our commercial rent dataset to shops in close proximity to shopping streets that we have footfall data for[5].

[4] Both Saturdays do not fall in a holiday period and are not preceded by bank holidays. Furthermore, on these days there is no heavy rainfall or other extreme weather conditions.
[5] We do not consider this as a selection problem since our study aims at estimating the effect of footfall on the productivity of shops located in city shopping districts and not simply anywhere in space.

The sectoral classification of the shops in the Strabo dataset is not very detailed. On the other hand, Locatus data provides information on several shop attributes for each shop (shop name, address, brand is a chain etc.) and includes a very detailed sectoral classification up to the branch level (e.g. it distinguishes between clothing shops for males and females). In order to recover more information on shop individual characteristics, we have matched the shops from the two datasets one to one. We only used shops from the two datasets that the year of the Strabo rental transaction and the year that the shop was observed by Locatus coincided or the former exceeded the latter by one, two or three years. In addition, the matching criteria include different geographical and shop characteristics. Specifically, the matching is based on different combinations of building identifiers, the full shop names or the first few letters of the name, the address numbers, the detailed postal code and the sectoral codes[6].

Information about the shopping streets (length, width, intersections) has been inferred from the above-discussed *Administration of Buildings and Addresses* dataset and the exact shop coordinates from *Locatus* (and *Strabo)* datasets. In essence, we created manually a GIS polyline shapefile with all shopping streets that we have footfall data available[7]. We have defined *shopping streets* as continuous relatively straight streets with shops in either or both sides of the street. We have matched each shop to the nearest shopping street for which we know street length, average street width, street intersections and we were also able to approximate the variability of street width by calculating the street width for each shop separately[8].

B. Descriptives

In this section, we present descriptive statistics for the main variables that we include in our analysis. Our main dependent variable is the annual rental price. Table 1 summarises the descriptive statistics for the Strabo-dataset. We show that the rental price has a mean of €51,449 with a substantial variation of €73,163. Our main independent variable of interest, (daily) footfall, also exhibits substantial variation, which ranges from 200 to 79,000 potential shoppers per day. The mean daily footfall is 13,552 people.

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Shops vary substantially in terms of size. However, the majority of the shops are relatively small, with a mean of 190m² and a median of 135m². Very few (0.6 percent) of these shops are sublet. Few (3.7 percent) are located inside a mall[9]. We also have information for the total building surface area, if the building was new or renovated when the transaction took place and the construction year. Most buildings of our sample (56.5 percent) were built before the Second World War. It is then not surprising that 48 percent of shops are located in historic

[6] See for more information on the matching Appendix A.1.
[7] Some examples of shopping streets are depicted in map A2 in Appendix A.1
[8] Shopping street width was calculated using the distance to the closest building to the building that each shop is located.
[9] We consider the shops that are located at the inner part of a building as opposed to shops located beside the outside street, based on the GIS building map.

districts. Another important control is the distance to the nearest train station. Although the mean distance is 1.2km, the median distance is 747m. This is a relatively short distance, which may reveal the preference of retailers to be located close to public transport nodes. It also demonstrates that shopping streets are often located in the centres of cities with excellent railway accessibility. Finally, 4.6 percent and 6.9 percent of the total number of shops have a water body within a distance of 50m and 100m respectively.

Shopping streets length ranges from approximately 44 to 1,270m. The street length mean and median are 431 and 359m respectively. Street width is on average 15.4m (which seems a reasonable figure). We have set the minimum width at 3m, which applies to small alleys in historic districts. We then have 3,102 observations located to 682 different shopping streets with 831 shopping street intersections.

TABLE 1 — DESCRIPTIVE STATISTICS OF STRABO DATASET

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	mean	sd	min	max
Rent *(euro/year)*	51,449	73,163	4,800	2,700,000
Rent *(euro/year/m^2)*	322.833	220.509	30	3000
Footfall *(potential shoppers per day)*	13,552	10,274	200	79,000
Size of property *(in m^2)*	190.4	206.1	25	4,000
Building surface area *(in m^2)*	1,275	4,490	20.44	86,771
Building – new	0.00387	0.0621	0	1
Building – renovated	0.00645	0.0800	0	1
Sublet property	0.00613	0.0780	0	1
Construction year < 1940	0.565	0.496	0	1
Construction year 1940-1949	0.0193	0.138	0	1
Construction year 1950-1959	0.0883	0.284	0	1
Construction year 1960-1969	0.0516	0.221	0	1
Construction year 1970-1979	0.0609	0.239	0	1
Construction year 1980-1989	0.0645	0.246	0	1
Construction year 1990-1999	0.0758	0.265	0	1
Construction year ≥2000	0.0587	0.235	0	1
Construction year missing	0.0161	0.126	0	1
Shopping street length *(in m)*	430.8	270.5	43.92	1,269
Shopping street width *(in m)*	15.36	10.15	3	116.6
Property is in mall	0.0374	0.190	0	1
Distance to nearest intersection *(in m)*	67.03	87.21	0.684	988.3
In historic district	0.478	0.500	0	1
Distance to station *(in m)*	1,206	1,928	65.97	18,280
Water within 50m	0.0461	0.210	0	1
Water 50-100m	0.0687	0.253	0	1

Note: The number of observations is 3,102.

In Table 2 we report descriptive statistics for the Locatus dataset, which entails the universe of shops in the Netherlands in the period 2003-2015. It is shown that about 6 percent of the shops are vacant. If we look at the distribution of construction years, it seems that compared to the Strabo dataset, fewer observations are in historic buildings (those with

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construction years before 1940). The descriptives of the locational variables are very comparable to the descriptives presented in Table 1.

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TABLE 2 — DESCRIPTIVE STATISTICS OF LOCATUS DATASET

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	mean	sd	min	max
Building is vacant	0.0625	0.242	0	1
Footfall *(potential shoppers per day)*	12,333	10,642	100	102600
Building surface *(in m^2)*	175.0	1,076	0.00012	27,694
Construction year < 1940	0.178	0.383	0	1
Construction year 1940-1949	0.0136	0.116	0	1
Construction year 1950-1959	0.0858	0.280	0	1
Construction year 1960-1969	0.155	0.362	0	1
Construction year 1970-1979	0.183	0.387	0	1
Construction year 1980-1989	0.113	0.316	0	1
Construction year 1990-1999	0.125	0.331	0	1
Construction year ≥2000	0.147	0.354	0	1
Distance to intersection *(in m)*	87.57	170.588	2.097	3,807.9
Shopping street length	404.0	245.4	21.09	1,269
Shop in department store	0.0612	0.240	0	1
Shopping street width *(in m)*	12.99	10.93	3	50
In historical district	0.393	0.488	0	1
Water within 50m	0.0509	0.220	0	1
Water in 50-100m	0.0743	0.262	0	1
Distance to station *(in km)*	1,583	2,752	1.980	18,534

Note: The number of observations is 416,675.

IV. Results

A. Effects of footfall on rents

Table 3 reports the results of fully parametric regressions where we regress the logarithm of shop rental prices on the logarithm of daily footfall. The specification in column (1) is an ordinary least squares regression of log rental price on log footfall, size of the rental property and shop location characteristics, in line with equation (1) in Section II.A. The elasticity of footfall with respect to rental price is 0.33. The property and building elasticities with respect to rental price have the expected sign and magnitude.[10]

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The specification in column (1) might suffer from omitted variable bias due to the omission of unobserved features of a shop location that are correlated to footfall. For example, some shopping areas are more attractive due to the proximity to a museum, school and other neighbourhood-specific amenities. The relevance of such factors is clear from the positive (and statistically significant) coefficient of the historic district dummy. A partial solution to this problem is the inclusion of shopping district fixed effects in column (2). This may mitigate some of the aforementioned endogeneity issues. Although the footfall

[10] The logarithm of the distance to the nearest station is highly significant and has a counterintuitive sign, because it may be negatively correlated with positive shopping street characteristics, such as whether the shop is in a pedestrian area.

coefficient remains virtually unchanged, unobservable characteristics at a smaller spatial scale might still cause omitted variable bias. For this reason, we also include shopping street fixed effects in column (3), Table 3. In this specification, we essentially exploit the variation in footfall *within* shopping streets. Although the footfall coefficient in column (3) is slightly smaller, the results are very robust.

In our sample, shopping street length varies from 44 to 1,269 suggesting that there are still some unobservable factors that vary within shopping streets. Examples of such variables could be a small square with a fountain or a sculpture located in the middle of a shopping street or the view to the canals that might vary within the shopping street. In order to deal with such factors columns (4)-(6) exploit variations between shopping streets close to intersections, by including shopping street intersection fixed effects. In columns (4) and (5), we include fixed effects for the shop locations that are within a distance of 100m and 50m from a shopping street intersection, respectively. It is plausible that shops located very close to an intersection are essentially identical controlling for property and building characteristics. Columns (4) and (5) suggest that when we use this identification strategy the estimated coefficient for footfall is reduced to 0.23 and 0.22, respectively.

Finally, one could argue that even when comparing the rental prices of shops on the different sides of a corner, shopping street width[11] is an important omitted variable which could affect both footfall and rental prices. The relationship between shopping width and footfall may be mechanical, because street width puts an upper bound on footfall. Moreover, shopping street width might affect the visibility of a shop, the supply of stock material and even the noisiness of the street caused by pedestrians or cars. Therefore, the inclusion of a shop-specific shopping street width variable is an important improvement. Additionally, some shops are located in the interior of a building (as opposed to shops located besides the street) and they are considered as shops inside malls. That could be another important omitted variable that could affect both footfall and rental prices. In column (6), Table 3, we include in addition to 50m intersection fixed effects shopping width, length and a dummy if a location is inside a mall. The estimated coefficient for footfall is highly statistically significant and its elasticity is 0.2. Although this is the most conservative estimate, it is considerably higher than the elasticities usually found in the literature on agglomeration economies. This result suggests that the net externality (including crowding and spatial competition effects) is very prominent.

[11] Shopping street width is calculated for each shop individualy. Therefore, we control for the fact that street width may vary within each shopping street.

TABLE 3 — REGRESSION RESULTS FOR RETAIL RENTS

(Dependent variable: the log of rent per m²)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Footfall *(log)*	0.330***	0.325***	0.306***	0.231***	0.220***	0.201***
	(0.0219)	(0.0178)	(0.0300)	(0.0257)	(0.0337)	(0.0349)
Size of property in m^2 *(log)*	0.587***	0.606***	0.608***	0.628***	0.622***	0.620***
	(0.0187)	(0.0138)	(0.0177)	(0.0172)	(0.0243)	(0.0241)
Building surface area in m^2 *(log)*	0.0397***	0.0309***	0.0351***	0.0515***	0.0557***	0.0559***
	(0.00931)	(0.00883)	(0.0126)	(0.0126)	(0.0162)	(0.0165)
Building – new	0.00358	-0.0621	0.0617	0.0639	-0.0707	-0.0728
	(0.160)	(0.141)	(0.111)	(0.137)	(0.281)	(0.279)
Building – renovated	0.429***	0.365***	0.246***	0.211**	0.124	0.132
	(0.103)	(0.0791)	(0.0750)	(0.107)	(0.0898)	(0.0916)
Sublet property	-0.0190	-0.00808	-0.0633	-0.106	-0.159	-0.156
	(0.0867)	(0.0761)	(0.0980)	(0.0989)	(0.0976)	(0.0953)
Property is in mall						0.0256
						(0.135)
Shopping street width in m *(log)*						-0.00636
						(0.0310)
Shopping street length in m *(log)*						0.0624**
						(0.0290)
Water within 50m	-0.0336	-0.143***	-0.127*	-0.0116	0.0349	0.00822
	(0.0506)	(0.0548)	(0.0684)	(0.116)	(0.110)	(0.107)
Water 50-100m	0.0346	-0.0535	-0.105**	0.0391	0.0367	0.0229
	(0.0559)	(0.0375)	(0.0424)	(0.0604)	(0.0835)	(0.0856)
Distance to station *(log)*	0.0590***	0.0283	0.0193	-0.0361	-0.0330	-0.0208
	(0.0183)	(0.0447)	(0.0681)	(0.0596)	(0.0504)	(0.0541)
In historic district	0.0665*	-0.0590	0.0613	0.0615	0.0309	0.00876
	(0.0369)	(0.0789)	(0.102)	(0.0696)	(0.0967)	(0.0915)
Construction year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Shopping district fixed effects	No	Yes	—	—	—	—
Shopping street fixed effects	No	No	Yes	No	No	No
Intersection fixed effects	No	No	No	Yes	Yes	Yes
Observations	3,102	3,102	3,102	2,629	1,870	1,870
R^2	0.581	0.708	0.809	0.848	0.871	0.872

Notes: Footfall is measured as the number of shoppers per day. In column (4) we include observations within 100 meters of a shopping street interaction. In columns (5) and (6) we reduce this to 50 meters. Robust standard errors are clustered at the shopping street level and in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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B. Effects of footfall on vacancy rates

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TABLE 4 — REGRESSION RESULTS FOR VACANT SHOPS
(Dependent variable: building is vacant)

we report results for the incidence of buildings to be vacant. Because we have a sufficiently large number of observations, we estimate linear probability models that deliver consistent results. We estimate a similar set of regressions as in the previous subsection. Column (1) is a naïve regression of the shop being vacant on footfall, the surface area of the building, construction year dummies, location attributes and year fixed effects. The coefficient suggests that doubling footfall leads to a 2 percentage points reduction in vacancies. The effect is slightly higher when we include shopping district fixed effects in column (2). In column (3), we only include shopping street fixed effects instead, leading to a similar effect: doubling footfall leads to an increase in the probability of being vacant of 2.6 percentage points.

In the last three columns we focus on our preferred identification strategy where we only include observations close to intersections of shopping streets. In column (4) we show that if we only include observations within 100 metres of an intersection. It is shown that the impact of footfall on vacancy rates is very similar: doubling footfall seems to imply a decrease in the probability being vacant of 2.2 percentage points. This effect is essentially the same once we reduce the distance to 50 metres of an intersection between shopping streets (column (5)) and when we include shopping street characteristics.

Hence, these results confirm that footfall is an important determinant of location choices of retail firms. It indicates that the most attractive locations in terms of footfall have a lower probability to be vacant, in line with what we suggest in Section II.B. Especially in the market for commercial properties, rents may be measured with error and parts of rents may be unobserved due to incentives. It is then reassuring that the analysis of vacancy rates delivers similar results.

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TABLE 4 — REGRESSION RESULTS FOR VACANT SHOPS

(Dependent variable: building is vacant)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Footfall *(log)*	-0.0309***	-0.0326***	-0.0360***	-0.0320***	-0.0320***	-0.0322***
	(0.00141)	(0.00141)	(0.00206)	(0.00183)	(0.00232)	(0.00244)
Building surface area in m² *(log)*	0.00230**	-0.000644	0.000185	-0.000757	0.000969	0.000999
	(0.000930)	(0.000761)	(0.000690)	(0.000717)	(0.000901)	(0.000900)
Property is in mall						0.00904
						(0.00702)
Shopping street width in m *(log)*						-0.00664***
						(0.00244)
Shopping street length in m *(log)*						0.00230
						(0.00187)
Water within 50m	0.00695	0.0134**	0.0118**	0.0177	0.00985	0.00914
	(0.00963)	(0.00550)	(0.00552)	(0.0110)	(0.0120)	(0.0119)
Water 50-100m	0.00228	0.00958***	0.00735*	0.000959	0.00418	0.00382
	(0.00427)	(0.00342)	(0.00407)	(0.00554)	(0.00715)	(0.00717)
Distance to station *(log)*	-0.00616***	-0.00316	-0.00381	-0.00329	-0.00700	-0.00697
	(0.00118)	(0.00379)	(0.00558)	(0.00684)	(0.00582)	(0.00582)
In historic district	0.00486*	0.0102	0.0115	0.0165*	0.0265*	0.0242
	(0.00261)	(0.00848)	(0.00822)	(0.00933)	(0.0160)	(0.0158)
Construction year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Shopping district fixed effects	No	Yes	—	—	—	—
Shopping street fixed effects	No	No	Yes	No	No	No
Intersection fixed effects	No	No	No	Yes	Yes	Yes
Observations	416,675	416,675	416,675	334,782	221,223	221,223
R^2	0.018	0.028	0.043	0.045	0.051	0.051

Notes: Footfall is measured as the number of shoppers per day. In column (4) we include observations within 100 meters of a shopping street interaction. In columns (5) and (6) we reduce this to 50 meters. Robust standard errors are clustered at the shopping street level and in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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V. Counterfactual analysis

A. How much footfall does one shop generates?

In the Results Section, we have estimated the effect of footfall on shop rents, vacancy rates and housing prices (in progress). These estimates confirm the positive effect of footfall for the retail sector while we take into account potential negative effects of footfall for residential housing. Having shown this net positive externality generated by footfall, a naturally subsequent question is what are the determinants of footfall. While we could think of many such determinants as the accessibility to transportation and parking, historical and other urban amenities etc., we will focus our attention to the effect of an additional shop on footfall. The answer to this question can help us formulate our policy recommendations.

In order to regress footfall on the number of shops we need to define some spatial unit of measurement. On the other hand, we want to avoid averaging out the high degree of local variation in footfall that the main identification strategy of this paper is based on. This is why we use the 6-digit postcode level (PC6), which is equivalent to approximately one street[12], as our main unit of analysis. Alternatively, we also use the proximity to the footfall measurement points.

Since we no longer use individual shops as the unit of analysis, we need a different identification strategy than the one applied so far. Some potential endogeneity issues in this estimation could be simultaneous causality bias and omitted variable bias. Adding location characteristics seems to abate this latter issue. However, in order to adequetly address these concerns between footfall and the number of shops, we will adopt an instrumental variables' (IV) approach using historical maps of the building uses in 1832 in Amsterdam and Rotterdam. Using these digital maps, we classified the different historical building uses in four different types: residential, business, mixed and public uses. Using this classification, we matched each modern shop to the use that the same location had in 1832[13]. Then, we aggregated the number of shops and the number of each class of historical building uses for each PC6 and for the alternative unit of analysis based on the nearest measurement point of footfall.

TABLE 5 presents the descriptives for the analysis of the number of shops on footfall. As can be seen, almost all locations of modern shops were residential in 1832. This is driven by the fact that our sample comprises mainly shops in Amsterdam (77 percent) and considerably fewer in Rotterdam. Furthermore, 91 percent from these 6-digit postcode areas in Amsterdam are located in historical districts.

On the other hand, the city of Rotterdam was heavily bombed by German air forces in the beginning of World War II, which completely destroyed the old city center. This bombing destroyed about 25,000 houses which caused about 12% of the city's population to became

[12] In the Netherlands, the combination of postcode and house number is unique.
[13] We matched each shop to the nearest historical building use within 5m distance.

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homeless at that time (Koster et al., 2012). As a result, there are no historical districts in our sample of shops in Rotterdam and historical businesses are a better predictor of modern shops.

Whereas Table 5 shows that the majority of 1832 building uses were residential, there is still considerable variation in their composition. TABLE 7 shows the total number of historical building uses in all PC6 areas of our sample. While residential use is the dominant building use, we argue that conditional on the history of each city, the variation of 1832 building uses is exogenous to modern footfall. In order to impose this conditionality, we add a dummy variable for Amsterdam and historical districts, while we also estimated the same effect for Amsterdam and Rotterdam separately. For the case of Rotterdam, we have included the number of historical business uses as an instrument instead of residential uses. Finally, the same analysis holds at the level of areas based on the shop proximity to the footfall measurement points. These results and the first-stage of the IV estimates are presented in the Appendix.

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TABLE 6 presents the results of the regression of footfall on the number of shops. Column (1) is a naïve OLS regression without any control variables. The coefficient of the number of shops suggests that doubling the number of shops in a PC6 area would increase footfall by 35 percent. However, in column (2), where we add location and shopping street characteristics, this effect drops to 19 percent. Column (3) shows the results of a two-stage IV regression, using location characteristics as controls. The estimated coefficient of the number of shops is virtually unchanged compared to column (2), while adding shopping street characteristics (in column (4)) makes any difference between OLS and IV estimation to diminish completely. Finally, in column (5), we cluster the standard errors based on the 5-digit postcode level to control for any spillovers between neighbouring streets. The results still hold.

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TABLE 5 — DESCRIPTIVE STATISTICS FOR FOOTFALL ANALYSIS

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	mean	sd	min	max
Footfall *(potential shoppers per day)*	18,934	13,410	763.6	52,857
Number of shops	6.231	4.466	1	30
Number of 1836 residential use	5.450	4.445	0	27
Number of 1836 businesses	0.355	0.861	0	5
Number of 1836 mixed use	0.602	1.207	0	8
Number of 1836 public use	0.127	0.438	0	3
Distance to nearest station	1,118	632.2	298.1	4,296
Historical district	0.701	0.459	0	1
Distance to water <50m	0.194	0.358	0	1
Distance to water 50-100m	0.254	0.384	0	1
Amsterdam dummy	0.769	0.422	0	1
Shopping street inside	0.00159	0.0214	0	0.333
Shopping street width	11.11	7.438	3.236	39.18
Shopping street length	483.0	203.9	62.45	1,175

Note: The number of observations is 255, which refers to the number of PC6 areas in Amsterdam and Rotterdam. Only shops that are within 5m of an 1836 historical building have been used for the aggregate PC6 level. All variables refer to averages over PC6.

TABLE 6 — REGRESSION RESULTS FOR FOOTFALL DETERMINANTS

(Dependent variable: log footfall)

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Number of shops (log)	0.353***	0.190**	0.205***	0.193**	0.193*
	(0.0709)	(0.0746)	(0.0737)	(0.0843)	(0.110)
Amsterdam dummy	-0.147	-0.779***	-0.964***	-0.777***	-0.777**
	(0.110)	(0.241)	(0.225)	(0.238)	(0.388)
Historical district		1.318***	1.242***	1.315***	1.315***
		(0.202)	(0.215)	(0.201)	(0.330)
Average distance to nearest station		-0.0805	-0.151*	-0.0803	-0.0803
		(0.0951)	(0.0917)	(0.0934)	(0.144)
Average distance to water <50m		-0.233	-0.118	-0.233*	-0.233
		(0.144)	(0.145)	(0.141)	(0.228)
Average distance to water 50-100m		-0.658***	-0.522***	-0.657***	-0.657**
		(0.153)	(0.157)	(0.150)	(0.262)
Average shop inside mall		2.942***		2.921***	2.921***
		(0.876)		(0.847)	(1.009)
Average shopping street width (log)		0.193		0.194	0.194
		(0.119)		(0.118)	(0.140)
Average shopping street length (log)		0.347***		0.347***	0.347***
		(0.0782)		(0.0774)	(0.109)
PC5 clustering	No	No	No	No	Yes
Observations	251	251	251	251	251
First-Stage F-statistic			165.4	165.5	122.4

Notes: In column (3)-(5) we instrument with the sum of the closest historical building use in 1832 that is considered residential use in each PC6 area. The first-stage regression is presented in Table 8. Robust standard errors are clustered at the shopping street level and in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B. *Should we subsidise shops to locate in shopping streets?*

In Section IV, we estimated the elasticity of retail rents with respect to footfall. In the previous Section A, we estimated the effect of the number of shops on footfall. In this section, we recover the average effect of a unit of footfall on retail profits and we also construct the counterfactual of new shops openings. The average effect is given by:

$$\frac{\mathrm{d}p_{ijt}}{\mathrm{d}f_{jt}} = \frac{\overline{p_{ijt}}}{\overline{f_{jt}}}\alpha$$

Based on a standard calculation using the mean rental price/m², the average footfall and our preferred estimate for the elasticity of footfall (0.2), we calculate that an additional unit of footfall generates an increase in retail profits of approximately 0.005 euros/year/m². This estimate is roughly one third of a naïve hedonic regression estimate. As we previously discussed, the presence of observed and unobserved local characteristics biases considerably such an estimation.

The first counterfactual estimation that we will consider is based on our estimates in Section A. We found that doubling the number of shops in an area causes an increase in footfall of 19 percent. If we consider the case that the number of shops rose by 20 percent, that would cause an increase in footfall of 3.8 percent. If we consider the mean footfall as the basis of a back-of-the-envelope calculation, the new shops would cause an increase of retail profits in the vicinity of 2.57 euros/year/m². If we then consider the average shop size in the Netherlands, then the benefit for an average shop would be almost 500 euros/year.

Recently, the media has focused on the shopping activity generated by the localization of certain types of department stores with low prices and huge variety (e.g. Wall Mart, Primarkt). We will now use the average footfall generated by "de Bijenkorf", a department store with long history in the Netherlands, which has been argued to generate a considerable increase in footfall in the areas that it is located. If we consider the average footfall in "de Bijenkorf" locations as exogenous (which is a very strong assumption), by further assuming that the nearby shops are too small to affect footfall, we can estimate the net benefit for the nearby shops. The average footfall in a "de Bijenkorf" location is 35,791 (based on our data), which would be translated to a benefit of 170.5 euros/year/m² for the shops in its vicinity. Such an estimate would yield that if department stores can produce sizeable footfall, policy interventions could subsidize such shops in order to stimulate this positive externality.

VI. Conclusions

The findings of this paper add to our understanding of retail agglomeration and yield valuable insight for policy. We have shown that footfall is a very important determinant of retail location choices. Thus, local policies should enhance these shopping externalities by fostering footfall in the shopping districts. Such policies could aim at increasing accessibility of shopping areas or increasing their attractiveness through amenities that could stimulate footfall and customer interchange. However, this analysis also finds that the number of shops in an area has a considerable potential to generate footfall. Therefore, shops or big shops that can generate more footfall in a shopping street could be directly subsidized.

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Appendix

A.1 Data appendix

The matching process between the Strabo and the Locatus shop datasets is based on shops that are in the Locatus dataset the same year or up to two years after the rental transaction. The two-year period is reasonable since a retailer usually keeps the shop vacant to refurbish the establishment after renting the property. In addition, Locatus gathers information on shops during the whole year (if a shop opened in March of a given year and Locatus recorded the shops in that area in April, the shop would appear in the Locatus dataset only in the following year).

The most accurate way for the matching is to use the exact name and building id's. This way we matched 5.64 percent of our Strabo data. Although the shop coordinates in the two datasets are very accurate, in some cases shops might be matched to another building close by[14]. Using the exact names, street number and the 6-digit postal codes (PC6), we matched 19.37 percent additional shops. In the Netherlands, the combination of each PC6 and each street number is unique. However, several observations have missing street numbers. This is why in a further step we use only the exact names and the PC6 codes and we match a further 1.93 percent of our sample. Hence, in total we matched 26.94 percent of the Strabo data using the complete name of each shop combined with some other exact location criteria.

Frequently, the name of the same shop does not appear identical in the two datasets. For this reason, we use the two first characters of the names in the two datasets for the rest of the shops (excluding articles such as “the” and other common words). Hence, using building id's, then PC6 and building numbers and finally, PC6, together with the first two letters of the shop names in the two datasets, we merged a further 5.64, 25.34 and 7 percent , respectively, adding up to a cumulative 64.92 percent of the shops in our sample.

The rest of the shops were merged based on the whole name and the 4-digit postal code (PC4), which approximately corresponds to a building block. This way we matched a further 3.19 percent of our sample and the final 31.88 percent was matched based on the exact names. We emphasise that we have double-checked manually all the matched observations and the results seem very accurate.

It should be mentioned that we applied this matching process in order to obtain the retail branch code for each shop and whether the shop is a part of a chain or not. However, our main analysis only requires the footfall information from the Locatus dataset, which can be matched very accurately without the need for a one-to-one shop matching. Nevertheless, our main results are not sensitive to this matching process.

[14] This depends on the area occupied by each building, which tends to be small in the central cities of the Netherlands.

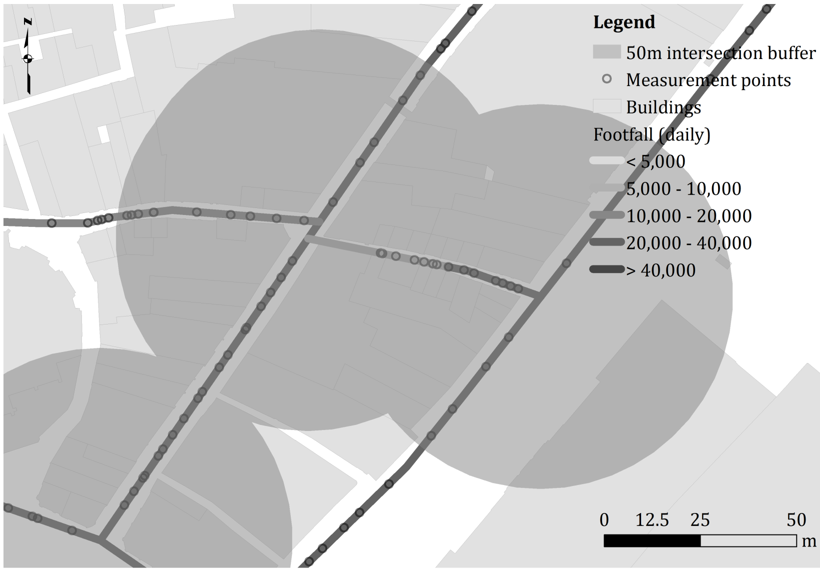

FIGURE A1 — SAMPLE MAP FOR THE AMSTERDAM CITY CENTRE

A.2. Tables appendix

TABLE 7 — DESCRIPTIVE STATISTICS FOR FOOTFALL ANALYSIS

	mean	sd	min	max
Number of 1836 residential use	131.4462	364.1612	0	3059
Number of 1836 businesses	18.10359	59.3179	0	646
Number of 1836 mixed use	28.91633	95.77789	0	1114
Number of 1836 public use	3.055777	11.92866	0	162

Note: The number of observations is 255, same as the number of 6-digit postcodes in Table 5.

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TABLE 8 — FIRST-STAGE REGRESSION RESULTS FOR FOOTFALL ANALYSIS

(Dependent variable: log number of shops)

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	(1) OLS	(2) OLS	(3) IV
Residential uses in1832	0.164***	0.165***	0.165***
	(0.0127)	(0.0129)	(0.0149)
Amsterdam dummy	-0.191	-0.259	-0.259
	(0.198)	(0.203)	(0.198)
Historical district	0.0674	0.0757	0.0757
	(0.190)	(0.189)	(0.185)
Average distance to nearest station	0.0484	0.0581	0.0581
	(0.0830)	(0.0790)	(0.0869)
Average distance to water <50m	0.0131	0.00384	0.00384
	(0.0874)	(0.0857)	(0.0939)
Average distance to water 50-100m	-0.000502	-0.0377	-0.0377
	(0.0892)	(0.0869)	(0.0829)
Average shop inside mall		-2.679**	-2.679**
		(1.130)	(1.026)
Average shopping street width (log)		-0.0722	-0.0722
		(0.0743)	(0.0775)
Average shopping street length (log)		0.106**	0.106
		(0.0536)	(0.0664)
PC5 clustering	No	No	Yes
Observations	251	251	251
R-squared	0.734	0.745	0.745

Notes: Columns (1)-(3) correspond to columns (3)-(5) in Table 6. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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TABLE 9 — REGRESSION RESULTS FOR FOOTFALL DETERMINANTS BY MEASUREMENT POINT

(Dependent variable: log footfall)

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	(1) OLS	(2) OLS	(3) IV	(4) IV
Number of shops (log)	0.449***	0.381***	0.305**	0.396***
	(0.146)	(0.128)	(0.135)	(0.136)
Historical district		0.815***	0.553***	0.817***
		(0.174)	(0.137)	(0.172)
Average distance to nearest station		-0.358**	-0.462***	-0.356**
		(0.147)	(0.143)	(0.149)
Average distance to water <50m		-0.227	-0.116	-0.228
		(0.187)	(0.196)	(0.184)
Average distance to water 50-100m		-0.631***	-0.601***	-0.629***
		(0.203)	(0.212)	(0.194)
Average shop inside mall		1.881*		1.856*
		(1.041)		(0.955)
Average shopping street width (log)		0.329**		0.331**
		(0.153)		(0.148)
Average shopping street length (log)		0.305**		0.304**
		(0.144)		(0.140)
Observations	151	151	151	151
First-Stage F-statistic			101.6	115.2

Notes: Columns (1)-(4) follow columns (1)-(4) in Table 6. In columns (3) we instrument with the sum of the closest historical building use in 1832 that is considered residential use in measurement point area. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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