# Empty Streets: The heterogeneous impact of the Corona crisis on the retail sector

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## Abstract

In this paper, the heterogeneous impact of the corona crisis on the retail sector is investigated by looking at footfall and retail rents. Using the unique wi-fi footfall data provided by Bureau RMC, it shows that the elasticity of footfall with respect to retail rents is around 0,22. For large cities, the effect is around 40% higher. The effect of the corona shock on footfall is also highly heterogeneous, with large cities being disproportionally affected. Combining these insights shows that central shopping districts in large cities are hit hardest by the corona crisis.

## Introduction

The corona virus and the ensuing measures to combat the spread of the virus have changed the world dramatically. Since the beginning of the global pandemic in early 2020 the whole society had to adjust to a completely new way of living. The act of "social distancing" changed how people interact and communicate with each other. Things that were previously commonplace are now restricted and things that were previously unheard of have become day to day business. Waring face masks in public and abstaining from giving hands and hugs has become normal, while ordinary things like going to a party have become a distant memory. The fact that this goes against our human nature to meet up and interact with others in person, makes this a strange but fascinating time.

This disruption of society has understandably a large effect on the economy. In the world economic outlook of the IMF, the world economy is projected to shrink by 4.9% (IMF, 2020) and this projection is plagued by uncertainty over how the coronavirus will develop in the near future. Figures for the Dutch economy on the second quarter of 2020, showed an unprecedented shrinkage of the economy of 8.5%. This is the largest quarterly decrease in GDP ever measured in the Netherlands (CBS (1), 2020).

All sectors have been hit hard by the corona crisis, however some sectors are more directly affected by the corona measures. One of the most directly noticeable is the retail sector. Shopping streets that were previously bustling with people became a shadow of their former selves. Shopping districts which were the epicentre of life, suddenly felt barren. From mid-March to the start of June, restaurant, bars, and cafés were prohibited to (physically) welcome customers and even some non- food retailers voluntarily closed their shops to decrease the change of contamination (Schelfaut, 2020). This effectively brought down the retail revenue of these (physical) shops and bars to zero. However, in later weeks most shops opened their doors again with extra protective measures, but the decrease in shopping footfall can still be felt. Since the amount of footfall near a shop is a good predictor of a shops potential retail revenue, this decrease in footfall is expected to have a negative impact on retail revenue (Graham, 2016). Following this line of reasoning, it could be expected that the relation between footfall and retail profits is close to a one. The reduction in footfall in combination with threats already present before the corona crisis like the growth of e-commerce sketches a bleak future for the retail sector.

This paper tries to quantify the effect of the decrease in footfall on the retail sector. Since large scale datasets on individual shop profits are hard to obtain, this paper will look at the indirect measure of retail rents. This is a convincing substitute, because retail rents and retail profits are highly correlated. When there is a competitive market for retail space, retailers that benefit from footfall will bid up against each other and the one who profits the most from footfall and subsequently will have the highest revenue, will be able to bid the most for the retail space. Therefore, high retail revenue will result in high retail rents. When the relationship between rents and footfall is established, the impact of the decrease in footfall can be estimated by using this estimate and multiplying it with the decrease in footfall caused by the corona crisis.

This paper will continue by first giving an overview of relevant literature concerning retail rents and footfall. This will be followed by a description of the data, which will give special attention to our unique way of measuring footfall. This will be followed by the regression results and an impact analysis of the corona crisis. Wrapping everything up is a conclusion with a policy recommendation.

## Literature review

The idea that footfall has a large impact on rents and sales is widespread in the real estate market and is often noted out by real estate agents to say something about the attractiveness of a retail unit. However, research on footfall is limited. In the shopping marketing literature, retail performance and revenue are thought to depend on the conversion rate, attraction rate and footfall density. Footfall density is a function of location, while the attraction rate is the shop's ability to encourage potential shoppers to enter the shop. The conversion rate is the shop's ability to convert these visitors into buyers. Based on anecdotal evidence the conversion and attraction rate are thought to be relatively stable, so footfall is the main determinant of retail revenue (Graham, 2016). This gives evidence for the hypothesis that a 1% decrease in footfall is expected to decrease retail revenue by a similar percentage, since footfall is the most important determinant of potential revenue.

A recent paper by Koster, Pasidis, & Van Ommeren (2019) is the first paper with a large dataset to look into the relationship between footfall and retail rents in the context of shopping streets. This paper on footfall is closely connected with the literature on retail agglomeration and shopping externalities. The researchers of this paper see footfall as a novel way to measure these shopping externalities.

The paper by Koster, Pasidis & Van Ommeren (2019) starts with the observation that retail facilities are highly clustered in shopping streets in city centres and shopping malls in more suburban centres. Because there is a clustering of activity, this means that there are large agglomeration benefits present for retail facilities. These agglomeration benefits are identified as shopping externalities and are closely connected with trip-chaining behaviour of customers. The reasoning behind this is that customers that want to purchase something have to incur a fixed cost of making a trip to a retail area

(Stahl, 1982). When there are more shops clustered together, potential buyers can benefit from reduction in search and transportation costs by chaining purchases together in one trip. So, when there are several shops located together, shoppers can purchase all the different items they need in one trip, while if all the shops were spread out over space this would cost them a lot more time and energy.

Footfall is a way to measure these shopping externalities rather precisely since footfall captures almost exclusively shoppers that visit several stores. This is especially true for large shopping concentrations. The amount of footfall in front of a shop is therefore not a consequence of that individual shop, but it is a product of the ability of the shopping centre to attract trip-chaining shoppers.  This assumption is reasonable to make since ownership in Dutch shopping streets is highly fragmented (Koster et al., 2019).  Therefore, larger shopping centres with more shops have more possibilities for shoppers in terms of trip-chaining and therefore usually have more shopping footfall.

This research on footfall relates to different strands of literature. First, it ties into the subject of agglomeration benefits. Agglomeration forces have fascinated urban economics since the seminal work of Marshall in the late 19th century, who argued that labour market pooling, input and output sharing and knowledge spill overs were the main drivers of agglomeration of activity (Marshall, 1890). Ample evidence from later research has showed that agglomeration increases the productivity of firms. However, most research on this subject is based on the manufacturing sector, so research on agglomeration forces in the retail sector is rather limited. Research by Koster, van Ommeren, & Rietveld, (2014) showed that there is a large heterogeneity in the size of the agglomeration effect between different sectors. For the office sector the expenditure on agglomeration was 5,3%, while the retail sector has an expenditure on agglomeration of 20%, which indicates that agglomeration is much more important for shops than for offices. This can be attributed to the trip-chaining behaviour, which is less important for most office sectors.  Research on rent gradients by Teulings, Ossokina, & Svitak, (2018) shows that retail rents  decrease by 15% when distance to the centre of the shopping district increases by 100 meters, which indicates sizable agglomeration benefits. A similar pattern is found for footfall where increasing the distance to the city centre by 100-meter decreases footfall with 40%.

Other papers zoom into the benefits and drawback of clustering in the retail sector. Besides positive agglomeration effects, clustering can increase competition and drive out businesses. The US literature on the entry of big box shops, like Walmart and Target, gives examples where the competition effect is stronger than the agglomeration effect. The entry of a big box shop has a substantial negative effect on employment growth for small retail chains and stand-alone so-called mom-and-pop shops (Haltiwanger, Jarmin, & Krizan, 2010). However, this effect is highly local and only effects firms within the same detailed industry. Other sector retail  is mostly unaffected (Clapp et al., 2019; Haltiwanger et al., 2010).  However, when the big box store is a general merchandize store these is some evidence that it also has a negative effect on other sector retail stores. This is not surprising since a general merchandise store effectively competes with all retail stores because of their wide product range. For restaurants on the other hand, the positive agglomeration effects dominates no matter the type of big box entry (Haltiwanger et al., 2010). Research on the expansion of Walmart into groceries also shows that the competition effect is highly local and mostly affects same sector retail shops (Ellickson & Grieco, 2013).

Research on anchor stores also shows evidence of large shopping externalities. Through its name's reputation and the sheer size of the shop, anchor stores attract a lot of shopping traffic to its location. These anchor stores are the main attractors of footfall for a particular shopping centre or mall and therefore are important hubs to cluster around in order to benefit from the positive shopping externalities (Konishi & Sandfort, 2003). Consequently, if an anchor leaves a shopping district this will have a negative effect. This is supported by research on US shopping malls which showed that non-anchor tenant rents are estimated to decline by 25% when an anchor tenant leaves the mall. (Gatzlaff, Sirmans, & Diskin, 1994). A similar study which looked at the bankruptcy of retail firms shows that the liquidation of firms weakens the economies of agglomeration, since footfall generated by the liquidated firms falls away. This increases the probability of other geographically close firms to close down as well (Benmelech, Bergman, Milanez, & Mukharlyamov, 2019). This is supported by research from Shoag & Veuger, (2018) who find that big box bankruptcies decrease both the number of shops and the employment in the retail sector in the surrounding area.

## Data sources

For this research on footfall, rents and the effects of corona, an innovative dataset on shopping street footfall is used. This dataset provided by the retail research bureau called Bureau RMC is unique because unlike other footfall data sources used in the papers by Graham, (2016), Koster et al., (2019) and Teulings et al., (2018) it does not rely on manual counting of passer-by's. Instead of relying on manual counting on predetermined dates, Bureau RMC uses Wi-Fi sensors to automatically track shopping footfall. These sensors work in a way that they detect unique wi-fi signals emitted by telephones carried by people that walk by a particular place. This information is then used to count the amount of people that walked past. To comply with privacy regulation, the unique wi-fi signal of the telephone (MAC address) is anonymised so it cannot be traced back to individual telephones. To control for the fact that some shoppers do not carry a mobile phone, the raw data is corrected with a conversion factor to better reflect actual footfall. Since spatial-temporal and demographic factors, like mobile ownership rates, can influence the data (Soundararaj, Cheshire, & Longley, 2020), the sensors are calibrated at the time of installation by comparing the Wi-Fi footfall with a manually counted number.

This novel way of measuring footfall allows us to filter out footfall which is not relevant for the performance of shops. Since the wi-fi sensors detect how many times certain anonymised MAC addresses pass a shop, double counting can be avoided by filtering out the effect of people passing by several times during their shopping trip. This improves the measurement of footfall since the number of unique visitors is ultimately most important for the brand exposure of a shop. Another thing that can be filtered out is the residents in the immediate vicinity of the shop. Residents pass by the shop, however they do not provide economic value for the shop. By examining MAC addresses that recur daily during the morning and evening, residents can be filtered out. Wi-Fi signals emitted by non-footfall related objects like printers and other fixed devices are also filtered out. These data are used to construct a variable that shows the average number of passengers per day in a particular year.

The RMC network consists of around 400 different Wi-Fi sensors spread out over shopping districts in the Netherlands. In order to function, the Wi-fi sensors need an internet connection and access to electricity. This is provided by the shop where the sensor is placed. To comply with privacy regulation the shops need to give permission on the counting of footfall with the Wi-Fi sensors. Therefore, placement of the sensors is based on contracts with retailers, municipalities, and shopping cooperation's. This induces some heterogeneity within the coverage of cities, since certain municipalities have a contract with many sensors, while others only have one wi-fi sensor.

For the information on commercial retail rents, two different datasets are used. The largest dataset is obtained from the retail consultancy firm Strabo and this dataset is supplemented with additional data from a company called Vastgoeddata. Both datasets comprise of commercial rent transactions provided by real estate agents spread over the country. All observations are from the last decade (from 2010 till 2020). The Strabo dataset has 7007 observations and Vastgoedata has 1327 observations. For the latter dataset, the retail rent observations are based in cities with the highest density of RMC wi-fi sensors. For both datasets, the building year, the size of the retail unit and the transaction year are known. There is some overlap in observations between the two retail rent datasets. This overlap is determined based on transaction year, the exact address, and the rent price per m2. If these three variables were overlapping then the observation of Vastgoedata was removed from the dataset.

Table 1

**Tabulation of Dataset raw**

| Dataset | Freq. | Percent | Cum. |
|---|---|---|---|
| Vastgoeddata | 1327 | 15.92 | 15.92 |
| strabo | 7007 | 84.07 | 84.07 |
| Total | 8334 | 100.00 | |

## Spatial analysis

The transactions are marched with the nearest wi-fi sensor. So, a rent observation in location x got assigned the average yearly footfall of the nearest wi-fi sensor. Most Wi-fi sensors do not have data for the average daily footfall for all years in the observed timespan. To combat this, imputed footfall was used based on an average national trend of footfall. This national trend was supplied by Bureau RMC and is based on a basket of scanners that were in operation during the whole time-period.

The maximum distance between the wi-fi sensor and the rent transaction was set to 150, 100 and 50 meters, respectively.  Since connectivity adds value to retail real estate (Nase, Berry, & Adair, 2013), the distance between the retail transaction and the train station was calculated using the Euclidean distance. Besides that, the number of bus stations was calculated by counting the number of bus stops within 200 meters. This information was used to construct a dummy variable for bus stops. Data on the location of train stops was derived from the Dutch railway company NS and the location of bus stops was derived via the open street map plugin in QGIS. Information on monumental buildings (rijksmonumenten) derived from the Dutch ministry of education and culture (rijksdienst voor cultureel erfgoed) is also added to control for people who visit the city centre mainly for the interesting architecture and not for shopping. Research by Carlino & Saiz (2019) shows that cities with historic districts and architectural beauty attract more visitors. Cultural heritage also increases the attractiveness the city for residents which is indicated by the increased willingness to pay for residential buildings in cities with a lot of cultural heritage (van Duijn & Rouwendaal, 2013).  The number of monumental buildings within 200 meters is counted for all rent transactions and added to the variable list.

## Data description

As can be expected there is no one to one overlap between the retail rent observations and the Wi-Fi footfall. Certain shopping districts have a many retail rent observation but lack Wi-Fi footfall data and vice versa. It is self-evident that the maximum distance for the spatial join influences the number of observation (see table). The percentage wise division between Strabo and Vastgoedata observations stays relatively constant when changing the maximum distance to a Wi-fi scanner.

Table 2

**Number of observations**

| Distance to scanner | 150m | | 100m | | 50m | |
|---|---|---|---|---|---|---|
| | Freq. | Percent | Freq. | Percent | Freq. | Percent |
| Vastgoeddata | 334 | 19.22 | 253 | 20.74 | 124 | 22.14 |
| Strabo | 1404 | 80.78 | 967 | 79.26 | 436 | 77.86 |
| Total | 1738 | 100.00 | 1220 | 100.00 | 560 | 100.00 |

Looking at the distribution over the years it can be observed that the centre of gravity of the Strabo data is more in the early years of the decade while Vastgoedata has more observations percentage wise in the last years of the decade compared to the Strabo data (see Figure 1) .

Figure 1

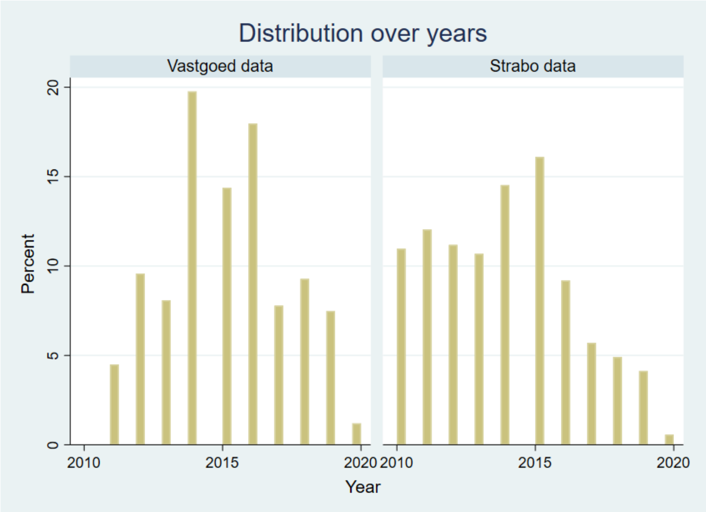



Table 3 shows the descriptive statistics of the dataset. The lowest rent per square meter can be found for a very large shop in the city of Enschede with a rent of € 9 per m2 while the highest rent per m2 is found at the popular shopping street Nieuwendijk in Amsterdam (€ 2692 per m2). The lowest average footfall per day is recorded in the small shopping district of Voorburg, while the Kalverstraat in Amsterdam is the busiest street. The average shop size is around 210 meters which is highly similar to the research of Koster et al. (2019). This reinforces the idea that most shops in the dataset are in typical European style high street locations characterised by a large concentration of small shops. There are a few shops that significantly deviate from the mean. However, these larger than 1000m2 shops make up limited part of the dataset and are mainly concentrated at highway locations characterized by DIY and furniture shops. For 10.9% of observations the building year is missing and almost 50% of all buildings are built before 1945. There is no substantial difference between the Vastgoeddata and the Strabo dataset in terms of the means of the descriptive statistics (see appendix).

Table 3

**Descriptive Statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Rent per m2 | 1738 | 280.184 | 214.079 | 9 | 2692 |
| Avg. Passanger per day | 1716 | 4861.867 | 4506.266 | 177 | 54295 |
| Size Shop (m2) | 1738 | 209.859 | 365.264 | 14 | 7000 |
| Building year before 1800 | 1738 | .109 | .312 | 0 | 1 |
| Building year 1800_1900 | 1738 | .154 | .361 | 0 | 1 |
| Building year 1900_1945 | 1738 | .223 | .417 | 0 | 1 |
| Building year 1945_1980 | 1738 | .221 | .415 | 0 | 1 |
| Building year 1980_2000 | 1738 | .127 | .333 | 0 | 1 |
| Building year after 2000 | 1738 | .057 | .232 | 0 | 1 |
| Building year missing | 1738 | .109 | .312 | 0 | 1 |
| Distance to train (meter) | 1588 | 991.747 | 1071.325 | 99 | 9944 |
| Dummy busstop (200m) | 1738 | .689 | .463 | 0 | 1 |
| Number of monuments (200m) | 1738 | 48.797 | 67.92 | 1 | 362 |

## Results

For testing the effect of footfall on retail rents, an ordinary least square specification (OLS) is used. This is in accordance with the paper of Koster et al. (2019). In that paper they find limited differences between the OLS specification and the more elaborated IV approach with historic long-lagged instruments. A log-log specification is used to arrive at the elasticity of footfall with respect to rents per square meter.

In Table 4 the most basis specification of the model is shown. The coefficient is highly statistically significant with a t value of 15.41 and it shows an elasticity of footfall with respect to retail rents of 0.31 which is of similar size as most earlier research. To place this in perspective: a 1% increase in footfall increases retail rents per m2 by 0.3% keeping everything constant. However, this finding is lower than the supposed 1 to 1 relationship supported by Graham (2016). This supports the idea that there is heterogeneity in the attraction and conversion rate. The spatial join of 100 meter is used since with this level of precision the number of observations is quite large and the join between the footfall wi-fi scanner and the rent observation is relatively precise. The average distance between a scanner and a rent observation is 54,3 meters. The regressions for the other distances can be found in the appendix.

Table 4

| VARIABLES | (1)<br>Baseline Model |
|---|---|
| Log Footfall | 0.3184*** |
| | (0.0207) |
| Constant | 2.8694*** |
| | (0.1692) |
| Observations | 1,198 |
| R-squared | 0.1657 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model (1) in Table 5 is an extended version of the baseline model. With the inclusion of several control variables and time fixed effects, the coefficient of footfall stays nearly unaffected. For most control variables the coefficients have the expected sign. The log of shop size has a negative effect on retail rents per m2 and for building year we observe that shops built between 1980 and 2020 have a significant negative effect on the log of retail rents per m2 compared to shops built before 1800. There is also evidence that the number of monuments within 200 meters significantly increases rents. Since a bunch of time dummies are significant it can be argued that there is a time trend present in retail rents.

Table 5

| Dependent: log of rent per m2<br>VARIABLES | (1)<br>Baseline control |
|---|---|
| Log avg footfall per day | 0.2944*** |
| | (0.0228) |
| Log shop size | -0.2713*** |
| | (0.0242) |
| Age building 1800_1900 | -0.0492 |
| | (0.0594) |
| Age building 1900_1945 | -0.0507 |
| | (0.0622) |
| Age building 1945_1980 | -0.0667 |
| | (0.0717) |
| Age building 1980_2000 | -0.1673** |
| | (0.0766) |
| Age building after 2000 | -0.0898 |
| | (0.0933) |
| BAGmissing | -0.0415 |
| | (0.0856) |
| Dummy busstop | -0.0203 |
| | (0.0352) |
| Log number of monuments | 0.0275** |
| | (0.0111) |
| Distance to trainstation | 0.0001*** |
| | (0.1768) |
| Constant | 4.4385*** |
| | (0.2442) |
| Observations | 1,090 |
| R-squared | 0.3257 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 6 different specifications are summarized. Model (1) is the baseline specification shown in the previous table. For readability purposes the dummy variables for building year and the year fixed effects are hidden. In model (2) city fixed effects are added to the regression. Fixed effects can be added to a regression when there is unobserved heterogeneity in the data and this heterogeneity stays constant over time. In the regression here, the city fixed effects take out the unique aspects of a city that stay constant over time. An example of this can be a reputation effect: even when controlling for other factors influencing rents, the rents in Amsterdam are higher just because the name Amsterdam carries a certain prominence and class. The inclusion of the 62 different City Fixed effects does decrease the size of the coefficient, however the coefficient stays significant and sizable. In a similar vein, shopping district fixed effects are added in model (3). This distinguishes between different large shopping districts in certain cities. This improves the specification since the reputation effect can be different for a shopping mall in the periphery of Amsterdam compared to the centre of Amsterdam. However, the inclusion of shopping district fixed effects does not really change the coefficient.

Although we took special care in addressing omitted variable bias with the inclusion of several control variables, it can still be the case that unobserved features of a shop location correlated with footfall influence the retail rent. An example could be the reputation of a certain street or its proximity to a specific amenity not included in the model. In model (4) shopping street fixed effects are therefore added to the further control for unobserved heterogeneity. The inclusion of the street level fixed effects decreases the coefficient quite a bit, but it stays relevant. This decrease in the coefficient can perhaps be attributed to the fact that there are limited streets with a lot of rent observations, the statistical space to run this regression is therefore limited. As can be expected, the control variables indicating local amenities like bus stops and monuments become insignificant after the inclusion of street fixed effects.

Table 6

| Dependent: Log Rent per m2<br>Join distance 100 meter<br><br>VARIABLES | (1)<br>Baseline<br>Control | (2)<br><br>City FE | (3)<br>Shopping<br>District FE | (4)<br><br>Street FE | (5)<br>Interaction<br>Large City | (6)<br>Interaction<br>Street FE |
|---|---|---|---|---|---|---|
| Log Footfall | 0.294*** | 0.221*** | 0.222*** | 0.139*** | 0.171*** | 0.129** |
| | (0.023) | (0.026) | (0.028) | (0.045) | (0.033) | (0.051) |
| Log Footfall* large city | | | | | 0.122*** | 0.047 |
| | | | | | (0.041) | (0.111) |
| Log size shop (m2) | -0.271*** | -0.291*** | -0.281*** | -0.323*** | -0.282*** | -0.323*** |
| | (0.024) | (0.019) | (0.020) | (0.021) | (0.020) | (0.021) |
| Distance to train (meter) | 0.000*** | 0.000 | -0.000** | 0.001*** | -0.000 | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Busstop | -0.020 | 0.085** | 0.076** | -0.059 | 0.069* | -0.057 |
| | (0.035) | (0.037) | (0.037) | (0.054) | (0.037) | (0.054) |
| Log number of monuments | 0.028** | 0.028* | 0.031 | 0.053 | 0.006 | 0.051 |
| | (0.011) | (0.016) | (0.027) | (0.050) | (0.028) | (0.051) |
| Constant | 4.438*** | 5.022*** | 5.243*** | 4.695*** | 5.306*** | 4.676*** |
| | (0.244) | (0.262) | (0.295) | (0.520) | (0.294) | (0.522) |
| Observations | 1,090 | 1,090 | 1,090 | 1,090 | 1,090 | 1,090 |
| R-squared | 0.326 | 0.275 | 0.248 | 0.347 | 0.255 | 0.347 |
| Building year dummies | YES | YES | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES | YES | YES |
| City Fixed effects | NO | YES | NO | NO | NO | NO |
| Shopping district Fixed effects | NO | NO | YES | NO | YES | NO |
| Shopping street fixed effects | NO | NO | NO | YES | NO | YES |
| Number of Cities | | 63 | | | | |
| Number of Shopping street | | | | 383 | | 383 |
| Number of Shopping district | | | 90 | | 90 | |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model (5) and (6) investigate the heterogeneity of the footfall coefficient between large and smaller cities, using the mean number of inhabitants as cut off point. In model (5) the effect of footfall on retail rents is almost 40% larger in the large cities than in smaller cities. This finding is in accordance with the literature on shopping externalities and agglomeration benefits. Since larger shopping centre have a lot of shops it shows that the agglomeration benefit is larger. For model (6) the statistical significance of the interaction term drops below conventional levels, and the explanatory power of the model runs into its limits. However, the normal footfall coefficient still stays significant at the 10% level.

The models with the different spatial join show a similar pattern. For the 150-meter model, the size of the coefficients is a bit smaller, which can be explained by the more imprecise nature of this spatial join.

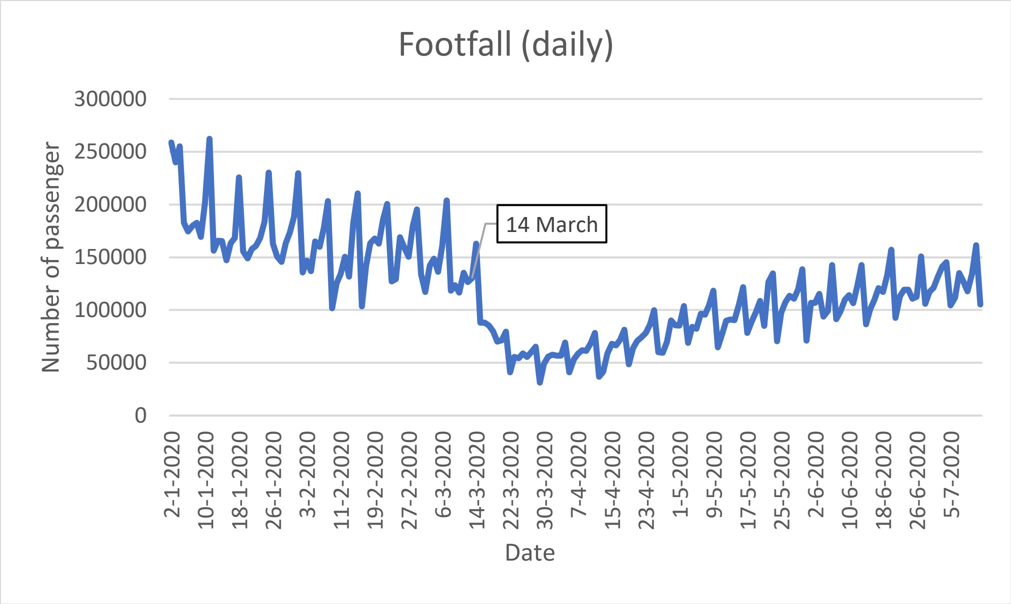
## Impact analysis

Having established a relationship between footfall and retail rents in the previous section, we use this information to get an estimate on the impact of the footfall reduction caused by the corona crisis. This is made possible by the unique Wi-Fi footfall data source provided by bureau RMC. Since most of the Wi-Fi scanners were online before and after the start of the corona crisis, the exact drop in footfall can be measured.

## Corona Footfall reduction

The number of passengers per day in the period from 1 January till 1 March 2020 is used to calculate a variable indicating the average number of passengers per day in the pre-corona period. The period used to calculate the average number of passengers per day in the post corona period is 14 March till 12 July. The demarcation of the pre and post corona period is based on the timeline of corona measures released by the Dutch department of Health. In the Netherlands the first reported corona infection took place in end of February, while the first drastic measures, such as the closing of schools and the closing of restaurants, were announced in the weekend of the second week of March (NU, 2020). The first weeks of March are excluded in both periods since this period was mostly characterized by an increased awareness of the virus, but drastic measures were still absent. Figure 2 shows the development over time of an index of 35 randomly selected Wi-Fi scanners and it supports the idea that the large footfall shock starts at 14 March. Besides this, it shows the distinct weekly pattern of footfall data with Saturday as the busiest day of the week.

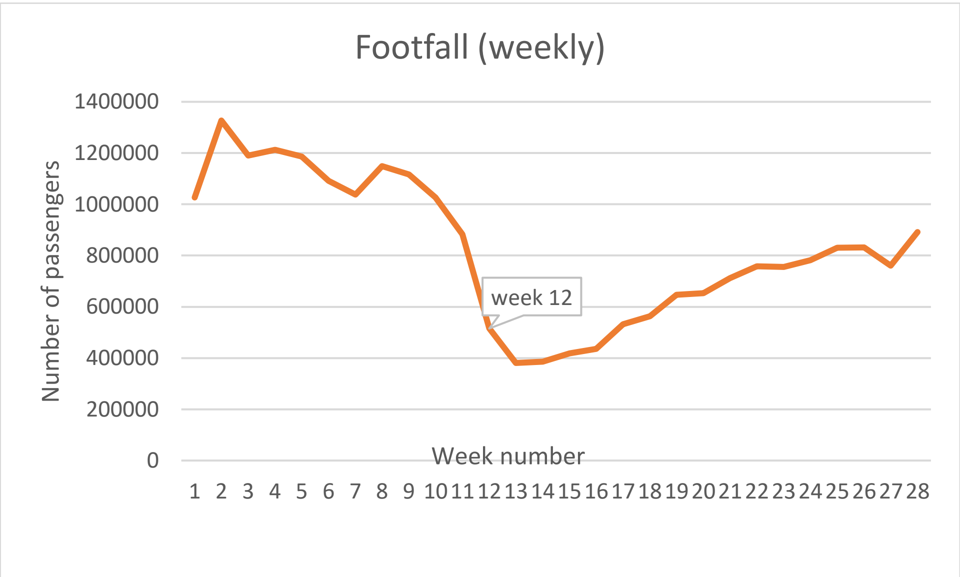
Figure 2




*Source: Citytraffic*

Figure 3 displays the weekly patterns, and it shows that footfall increases slowly after the initial shock of March and April. However, in July the footfall level is still substantially below pre-corona levels.

Figure 3



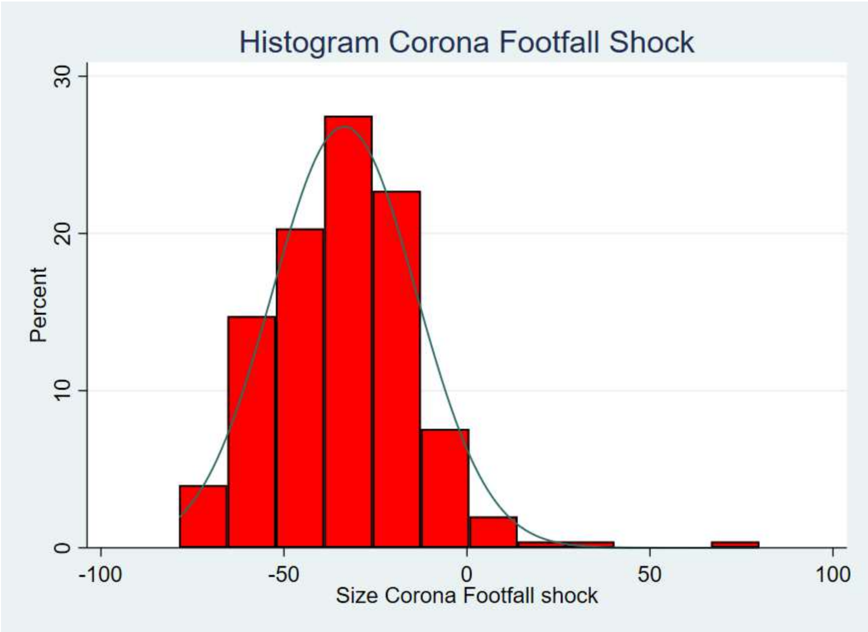

*Source: Citytraffic*

The size of the footfall reduction caused by corona is calculated by:

$$(1)\quad Corona\ footfall\ shock = \frac{(precorona - postcorona)}{precorona} * 100$$

The histogram in Figure 4 shows the distributions of the corona footfall shock for all the different wi-fi scanners (251 in total). Most observations have a negative corona footfall shock; however, the size of the effect varies significantly. The mean of the shock is -33.5% and the largest decrease in footfall is -78.6%. There are a few observations with an increase in footfall compared to pre-corona levels. These exceptions will be discussed in a later stage.

Figure 4



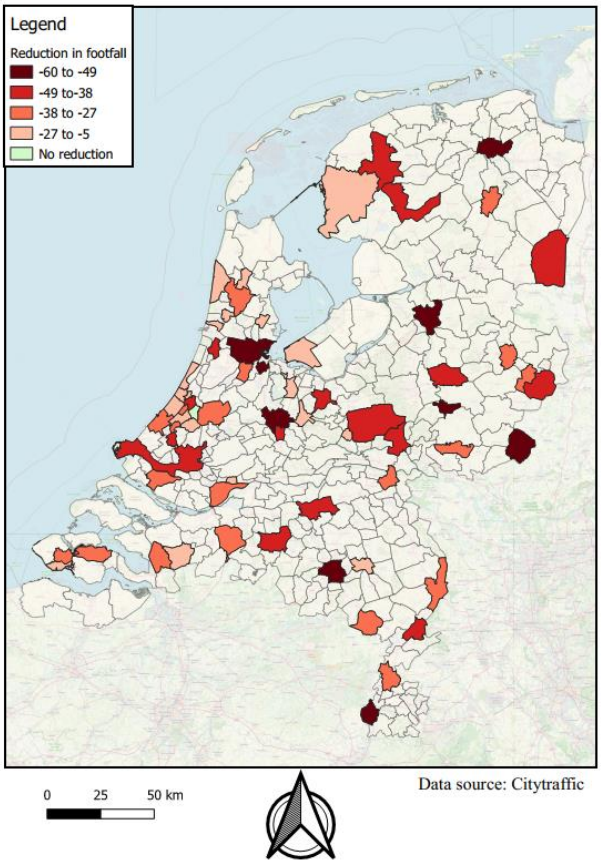

.

*Source: Citytraffic*

As seen in the figure above, the effect of corona on footfall is not homogeneous.. Figure 5 shows a map of the variation over municipalities. It can be observed that especially large cities, like Amsterdam, Utrecht and Groningen observe a decrease in footfall, whereas more peripheral regions have a lower reduction.

Figure 5

Reduction in footfall caused by Corona




However, the map of figure 5 does not tell the whole story, as it ignores the type of shopping district. The inner city of Amsterdam can have a rather different dynamic than a more peripheral shopping mall in Amsterdam Noord. Zooming into the level of shopping districts we do see the largest reduction in footfall happening in central shopping areas in the larger cities (see Table 7)

*Table 7: Top 10 biggest footfall reductions*

| Shopping district | Corona footfall shock |
|---|---|
| 1) Amsterdam Centrum | -67.7% |
| 2) Zutphen Centrum | -60.5% |
| 3) Winterswijk Centrum | -59.4% |
| 4) 's-Gravenhage Museumkwartier | -57.7% |
| 5) Utrecht Centrum | -56.8% |
| 6) Amsterdam Damrak | -56.0% |
| 7) Eindhoven Centrum | -55.1% |
| 8) Rotterdam Zuidplein | -53.6% |
| 9) Maastricht Centrum | -53.4% |
| 10) Zwolle Centrum | -50.3% |

*Source: Citytraffic*

To further investigate the footfall shock caused by corona, a basic OLS regression is employed. Model (1) of Table 8 shows that a large city has a 20% extra reduction in footfall compared to smaller cities. For model (2) shopping district type dummies are added to the model. These shopping area typification's are derived from the retail consultancy firm Locatus. They employ an extensive typology based on the size of a retail area and if the retail is the central shopping area of a city or a supporting shopping area (Locatus, 2016). For convenience, some categories for small shopping centres were merged into a large category called "small shopping centre" and the extra category "beach" was added to account for the unique dynamics of retail areas right next to the beach. The category large central shopping district (more than 400 shops) is the omitted category, so all coefficients are to be understood in relation to this category. What is striking is that all shopping area type dummy variables are positive and significantly different from the dynamics at large central shopping area's apart from the rather comparable medium/large shopping district. This means that the there is less footfall reduction in smaller shopping area's than in larger shopping concentrations. The largest positive coefficient can be found for locations characterised by large scale shops like home interior and DIY stores (home interior malls), which could give some support to the hypothesis that people used the corona quarantine to renovate their residence. Even when including all these shop area type dummy variables the effect of a large city on the corona footfall shock is still negative.

Table 8

| Dep: corona shock footfall<br>VARIABLES | (1)<br>Large city | (2)<br>Shopping district type |
|---|---|---|
| Large City | -20.740*** | -14.012*** |
| | (2.430) | (2.839) |
| Inner-city shopping street (supporting) | | 24.753*** |
| | | (5.193) |
| Home interior mall | | 32.326*** |
| | | (5.241) |
| Medium/large shopping district (central) | | 4.568 |
| | | (3.156) |
| Medium shopping district (central) | | 12.333*** |
| | | (3.186) |
| Medium/small shopping district (central) | | 30.769*** |
| | | (5.491) |
| Large shopping mall (supporting) | | 18.972*** |
| | | (5.155) |
| Beach | | 25.350*** |
| | | (5.758) |

| | | |
|---|---|---|
| Small shopping centre (supporting) | | 21.421*** |
| | | (4.458) |
| Constant | -27.668*** | -39.125*** |
| | (1.293) | (2.481) |
| Observations | 251 | 251 |
| R-squared | 0.226 | 0.462 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The regressions above give support for the hypothesis that the reduction in footfall was largest in the central inner-city shopping districts of large cities. More peripheral shopping districts such as supporting shopping malls and central shopping areas of small cities were affected less. Shopping areas with a special function like home interior malls also experienced a small shock in footfall reduction.

## Impact of corona on retail rents

Having established the relationship between footfall and retail rents and having investigated the impact of corona on footfall levels, we can combine both insights to estimate the impact of the corona crisis on the retail sector. For this analysis, the regression coefficients of model (5) of table 6 are used since this model looks at the heterogeneous impact of footfall on retail rents. Although this model does not include street fixed effects, it does include several control variables like the number of monuments and the connectivity variables, which should control for most of the differences between shop locations. Taken this into account the coefficients of model (5) are a good representation of the effect of footfall on rents, with perhaps a small upward bias.

The impact of corona is calculated by formula (2)

$$(2) Impact\ Corona = (Exp\ (coronafootfall\ shock) - 1) * (elasticity\ footfall + elasticity\ footfall\ large\ city * dummy\ large\ city)$$

Filling in with the coefficients from model (5) this results in:

$$(2) Impact\ Corona = (Exp\ (coronafootfall\ shock) - 1) * (0.171 + 0.122 * dummy\ large\ city)$$

Plotting the outcome of this formula geographically in a similar way as with footfall reduction results in figure 6. Since the relation between footfall and rents is not a 1 to 1 relation the impact of corona is lower than the figures for the reduction in footfall, but the effect is still very sizable. Another interesting fact is that the difference between large and smaller cities is much more pronounced in

Figure 6 than in Figure 5. This can be explained by the fact that large cities are disproportionately affected by the corona shock in two distinct ways. First, footfall is more important for rents in larger cities shown by the larger footfall coefficient. Secondly, the reduction in footfall is much more severe in larger cities than in smaller shopping centra. In table 9 the shopping districts which are affected the most are summarized, and it shows that central shopping area's in large cities are affected the most.

Figure 6

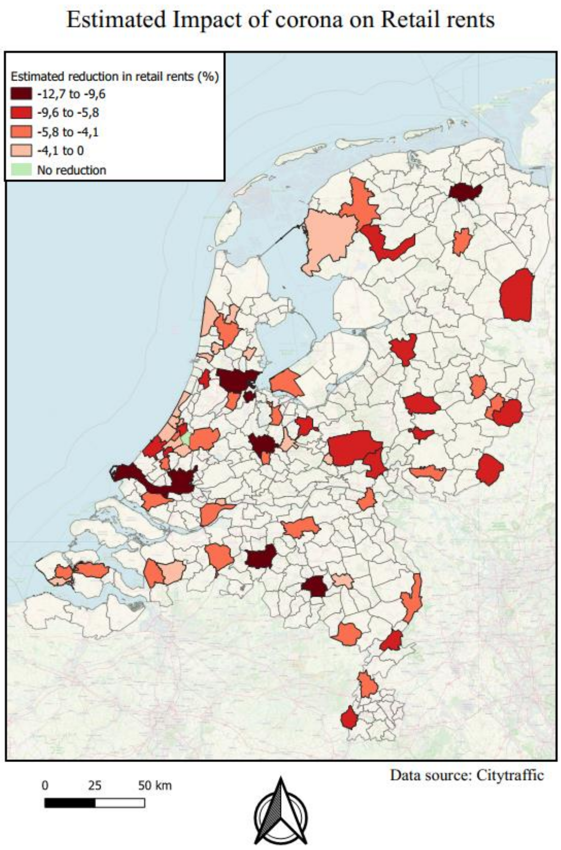



*Table 9: Top 10 largest negative corona impact on rents*

| Shopping district | Impact corona |
|---|---|
| 1) Amsterdam Centrum | -14.4% |
| 2) 's-Gravenhage Museumkwartier | -12.8% |
| 3) Utrecht Centrum | -12.6% |
| 4) Amsterdam Damrak | -12.6% |
| 5) Eindhoven Centrum | -12.4% |
| 6) Rotterdam Zuidplein | -12.2% |
| 7) Groningen Centrum | -11.6% |
| 8) Amsterdam 9 Straatjes | -11.1% |
| 9) 's-Gravenhage Stadsentrees | -11.1% |
| 10) Groningen WC Paddepoel | -9.8% |

*Source: Citytraffic*

To get a better feeling for the size of the impact displaced above, a simple thought experiment can shed some much-needed light on the situation. For a shop in the centre of Amsterdam it is expected that rent per m2 should be reduced by -14.4% to account for the corona footfall shock. The average shop size for observations in Amsterdam centre is 318 meters and the average rent per m2 is €603, – which result in an average rent of €191.754, -. A 14.4% reduction in rent amounts to an expected reduction in rent of €27.612, - to account for the corona footfall shock. However, because most retail rents have a large fixed component, retail rents do not immediately adjust to a new situation. So, there is some smoothing in the retail rent market (Chun, Eppli, & Shilling, 2001). This can be disastrous for retail shops. Following the connection between rents and retail revenue, their retail revenue is expected to decrease by €27.612, - In the meanwhile, rent do not adjust as quickly. Rigid rents are therefore a milestone around the neck which can drag retail shops down to bankruptcy. Bankruptcies also impose negative externalities on surrounding shops, because a bankruptcy weakens the economies of agglomeration and the shopping externalities (Benmelech et al., 2019). This can cause a chain reaction in bankruptcies in the shopping areas that are hit hardest by the corona footfall shock.

However, this paper only considers the effect of the footfall reduction on retail rents and does not look into the wider economic implications of the corona crisis. General consumer spending in the Netherlands decreased substantially in the first months of the corona crisis (CBS (2), 2020), and online sales increased significantly (ecommerceinholland, 2020). This can weaken the position of physical shops even further.

## Conclusion

In this paper, the heterogeneous impact of the corona crisis on the retail sector is investigated by looking at footfall and retail rents. This is made possible by the unique wi-fi footfall data provided by Bureau RMC. Since this footfall data source does not rely on manual counting, it provides a continuous insight in footfall development for al Wi-fi scanner's locations. Therefore, it is possible to monitor the exact decrease in footfall caused by the corona crisis rather precisely and zoom into the differences between shopping areas. Besides this, counting footfall with Wi-fi scanners improves the way footfall is measured, since it avoids double counting and non-relevant footfall. This improves the estimation of the footfall coefficients.

The main regression results show that the elasticity of footfall with respect to retail rents is around 0.22. This is in line with earlier research by Koster et al. (2019) although the coefficient is a bit lower especially for the street fixed effect model. This can partially be explained by the fact that the dataset of this research has a lower number of observations for every street compared to the research by Koster et al. (2019). This influences the statistical space for which the coefficients can be estimated. The research also shows that there is a heterogeneous effect of footfall on retail rents. For larger cities, the elasticity of footfall with respect to retail rents is around 40% higher.

This heterogeneity also works through into the reduction in footfall caused by Corona. Large central shopping districts in large cities experienced the largest reduction in footfall, whereas small peripheral shopping areas and specialized shopping areas like home interior malls are affected less by the corona footfall shock. When combining both insights, this research shows that large cities are disproportionally affected by the corona footfall shock. Large cities experience the largest reduction in footfall and the preference for footfall is highest in these cities.

Having a better understanding of the impact of the corona crisis on the retail sector helps policy design. This research shows that the impact is rather heterogeneous, and policy should reflect this. Although all retail shops face difficult times during the corona epidemic, some are affected more than others. The corona footfall shock can lead to bankruptcies and these bankruptcies influence surrounding stores. Therefore, there should be special attention for central shopping districts in large cities. This can be done by paying special attention to the rent burden. Local authorities can talk with retail property owners to discuss the probability to postpone or reduce the rent payments to give retail shops some breathing room in these difficult times.

However, a few words of caution are in order. The impact analysis is based on the elasticity of footfall on rents estimated for observations from before the corona crisis. It therefore assumes that this relationship stays the same during the corona crisis. It is very well possible that this relationship is also affected by the corona crisis. It is for example possible that, although the number of people visiting the shopping districts decreased, the number of people that make a purchase increased. This increases the economic value of an individual shopper and this would decrease the negative impact of corona. However, this hypothesis was out of the scope of this research paper. Future research should investigate these dynamics more thoroughly by also incorporating the attraction and conversion rate, since this is instrumental in further exploring the complex dynamics of footfall on retail revenues and rents. This addition will help to further demystify the enormous impact of the corona crisis on the retail sector.

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# Appendix

## Distribution of data

| | Dataset | | |
|---|---|---|---|
| | Vastgoed data | Strabo data | Total obs |
| 's-Gravenhage | 42 | 128 | 170 |
| 's-Hertogenbosch | 0 | 15 | 15 |
| Alkmaar | 50 | 74 | 124 |
| Almelo | 0 | 28 | 28 |
| Almere | 0 | 2 | 2 |
| Alphen aan den Rijn | 0 | 7 | 7 |
| Amersfoort | 0 | 31 | 31 |
| Amstelveen | 0 | 5 | 5 |

| | | | |
|---|---|---|---|
| Amsterdam | 19 | 20 | 39 |
| Apeldoorn | 0 | 29 | 29 |
| Arnhem | 0 | 19 | 19 |
| Assen | 0 | 11 | 11 |
| Bergen NH | 0 | 8 | 8 |
| Bergen op Zoom | 0 | 11 | 11 |
| Beverwijk | 0 | 1 | 1 |
| Breda | 0 | 65 | 65 |
| Delft | 0 | 5 | 5 |
| Deventer | 0 | 8 | 8 |
| Doetinchem | 0 | 21 | 21 |
| Dordrecht | 0 | 13 | 13 |
| Ede Gld | 0 | 21 | 21 |
| Egmond aan Zee | 0 | 4 | 4 |
| Eindhoven | 0 | 45 | 45 |
| Emmen | 0 | 6 | 6 |
| Enschede | 45 | 91 | 136 |
| Goes | 0 | 12 | 12 |
| Groet | 0 | 1 | 1 |
| Groningen | 0 | 19 | 19 |
| Haarlem | 0 | 6 | 6 |
| Heerenveen | 0 | 4 | 4 |
| Heerhugowaard | 0 | 7 | 7 |
| Heerlen | 0 | 14 | 14 |
| Helmond | 0 | 14 | 14 |
| Hengelo | 27 | 41 | 68 |
| Hilversum | 0 | 23 | 23 |
| Hoofddorp | 0 | 3 | 3 |
| Hoorn NH | 0 | 2 | 2 |
| Katwijk | 16 | 61 | 77 |
| Leeuwarden | 0 | 5 | 5 |
| Leiden | 30 | 132 | 162 |
| Maastricht | 0 | 42 | 42 |
| Middelburg | 5 | 2 | 7 |
| Nieuwegein | 0 | 1 | 1 |
| Nijmegen | 0 | 25 | 25 |
| Noordwijk | 9 | 23 | 32 |
| Noordwijkerhout | 0 | 4 | 4 |
| Oegstgeest | 0 | 8 | 8 |
| Oss | 0 | 7 | 7 |
| Purmerend | 0 | 2 | 2 |
| Rijnsburg | 0 | 9 | 9 |
| Roermond | 0 | 10 | 10 |
| Roosendaal | 0 | 11 | 11 |
| Rotterdam | 48 | 46 | 94 |
| Schoorl | 0 | 1 | 1 |
| Sittard | 0 | 16 | 16 |
| Sliedrecht | 0 | 5 | 5 |
| Sneek | 0 | 5 | 5 |
| Spijkenisse | 11 | 11 | 22 |
| Tilburg | 0 | 7 | 7 |
| Uden | 0 | 3 | 3 |
| Uitgeest | 0 | 1 | 1 |
| Utrecht | 16 | 40 | 56 |
| Veenendaal | 0 | 7 | 7 |
| Venlo | 0 | 5 | 5 |
| Vlissingen | 5 | 11 | 16 |
| Voorburg | 0 | 13 | 13 |
| Voorschoten | 0 | 3 | 3 |
| Wassenaar | 0 | 6 | 6 |

| | | | |
|---|---|---|---|
| Weert | 0 | 1 | 1 |
| Winterswijk | 0 | 3 | 3 |
| Zeist | 11 | 18 | 29 |
| Zoetermeer | 0 | 14 | 14 |
| Zoeterwoude | 0 | 6 | 6 |
| Zutphen | 0 | 5 | 5 |
| Zwolle | 0 | 21 | 21 |
| Total | 334 | 1404 | 1738 |

## Descriptive statistics

**Descriptive Statistics (all)**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Rent per m2 | 1738 | 280.184 | 214.079 | 9 | 2692 |
| Avg. Passenger per day | 1716 | 4861.867 | 4506.266 | 177 | 54295 |
| Size Shop (m2) | 1738 | 209.859 | 365.264 | 14 | 7000 |
| Building year before 1800 | 1738 | .109 | .312 | 0 | 1 |
| Building year 1800_1900 | 1738 | .154 | .361 | 0 | 1 |
| Building year 1900_1945 | 1738 | .223 | .417 | 0 | 1 |
| Building year 1945_1980 | 1738 | .221 | .415 | 0 | 1 |
| Building year 1980_2000 | 1738 | .127 | .333 | 0 | 1 |
| Building year after 2000 | 1738 | .057 | .232 | 0 | 1 |
| Building year missing | 1738 | .109 | .312 | 0 | 1 |
| Distance to train (meter) | 1588 | 991.747 | 1071.325 | 99 | 9944 |
| Dummy bus stop (200m) | 1738 | .689 | .463 | 0 | 1 |
| Number of monuments (200m) | 1738 | 48.797 | 67.92 | 1 | 362 |

**Descriptive Statistics (Strabo)**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Rent per m2 | 1404 | 284.178 | 222.809 | 17 | 2692 |
| Avg. Passenger per day | 1386 | 4912.287 | 4250.998 | 177 | 54295 |
| Size Shop (m2) | 1404 | 199.782 | 339.289 | 20 | 7000 |
| Building year before 1800 | 1404 | .108 | .311 | 0 | 1 |
| Building year 1800_1900 | 1404 | .157 | .364 | 0 | 1 |
| Building year 1900_1945 | 1404 | .212 | .409 | 0 | 1 |
| Building year 1945_1980 | 1404 | .214 | .41 | 0 | 1 |
| Building year 1980_2000 | 1404 | .12 | .325 | 0 | 1 |
| Building year after 2000 | 1404 | .054 | .226 | 0 | 1 |
| Building year missing | 1404 | .135 | .342 | 0 | 1 |
| Distance to train (meter) | 1254 | 836.582 | 425.994 | 99 | 2975 |
| Dummy bus stop (200m) | 1404 | .703 | .457 | 0 | 1 |
| Number of monuments (200m) | 1404 | 48.289 | 67.189 | 1 | 359 |

**Descriptive Statistics (Vatsgoeddata)**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Rent per m2 | 334 | 263.392 | 171.897 | 9 | 1000 |
| Avg. Passenger per day | 330 | 4650.103 | 5451.892 | 307 | 45401 |
| Size Shop (m2) | 334 | 252.219 | 456.835 | 14 | 6000 |
| Building year before 1800 | 334 | .114 | .318 | 0 | 1 |
| Building year 1800_1900 | 334 | .141 | .348 | 0 | 1 |
| Building year 1900_1945 | 334 | .269 | .444 | 0 | 1 |
| Building year 1945_1980 | 334 | .251 | .435 | 0 | 1 |
| Building year 1980_2000 | 334 | .156 | .363 | 0 | 1 |
| Building year after 2000 | 334 | .069 | .254 | 0 | 1 |
| Building year missing | 334 | 0 | 0 | 0 | 0 |

| | | | | | |
|---|---|---|---|---|---|
| Distance to train (meter) | 334 | 1574.314 | 2087.089 | 103 | 9944 |
| Dummy bus stop (200m) | 334 | .632 | .483 | 0 | 1 |
| Number of monuments (200m) | 334 | 50.931 | 70.979 | 1 | 362 |

## Correlation matrix

| Matrix of correlations | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| (1) log Rent per m2 | 1.000 | | | | | | | | | | | | |
| (2) log Avg passenger per day | 0.349 | 1.000 | | | | | | | | | | | |
| (2) log Avg pass per day inter | 0.303 | 0.316 | 1.000 | | | | | | | | | | |
| (4) log size shop | -0.396 | -0.042 | 0.050 | 1.000 | | | | | | | | | |
| (5) BAGbetween1800 1900 | 0.107 | 0.015 | -0.033 | -0.108 | 1.000 | | | | | | | | |
| (6) BAGbetween1900~1945 | -0.022 | -0.054 | 0.013 | -0.016 | -0.246 | 1.000 | | | | | | | |
| (7) BAGbetween1945~1980 | -0.096 | 0.001 | 0.061 | 0.119 | -0.235 | -0.285 | 1.000 | | | | | | |
| (8) BAGbetween1980~2000 | -0.067 | -0.015 | -0.041 | -0.026 | -0.159 | -0.192 | -0.184 | 1.000 | | | | | |
| (9) BAGafter2000 | -0.076 | -0.022 | -0.089 | 0.090 | -0.103 | -0.124 | -0.119 | -0.080 | 1.000 | | | | |
| (10) BAG missing | 0.000 | -0.003 | 0.006 | 0.058 | -0.156 | -0.189 | -0.181 | -0.122 | -0.079 | 1.000 | | | |
| (11) Distance to train | -0.036 | -0.206 | -0.083 | 0.046 | -0.049 | -0.005 | -0.030 | 0.178 | 0.024 | -0.060 | 1.000 | | |
| (12) Dummy busstop | -0.058 | -0.029 | -0.258 | 0.017 | -0.028 | -0.043 | 0.031 | 0.055 | 0.006 | 0.045 | 0.059 | 1.000 | |
| (13) log monuments (200) | 0.243 | 0.184 | 0.061 | -0.188 | 0.301 | 0.021 | -0.336 | -0.198 | -0.147 | -0.085 | -0.150 | -0.104 | 1.000 |

| Matrix of correlations | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 | -10 | -11 | -12 |
| (1) prijsm2win | 1000 | | | | | | | | | | | |
| (2) avgPassangerday | 0.429 | 1000 | | | | | | | | | | |
| (3) m2winkel | -0.136 | 0.000 | 1000 | | | | | | | | | |
| (4) BAGbefore1800 | 0.159 | 0.174 | -0.034 | 1000 | | | | | | | | |
| (5) BAGbetween~1900 | 0.052 | -0.004 | -0.074 | -0.167 | 1000 | | | | | | | |
| (6) BAGbetween~1945 | -0.051 | -0.093 | -0.045 | -0.202 | -0.246 | 1000 | | | | | | |
| (7) BAGbetween~1980 | -0.054 | -0.027 | 0.028 | -0.193 | -0.235 | -0.285 | 1000 | | | | | |
| (8) BAGbetween~2000 | -0.058 | -0.012 | 0.005 | -0.130 | -0.159 | -0.192 | -0.184 | 1000 | | | | |
| (9) BAGafter2000 | -0.060 | -0.027 | 0.172 | -0.084 | -0.103 | -0.124 | -0.119 | -0.080 | 1000 | | | |
| (10) BAGmissing | 0.011 | 0.014 | 0.025 | -0.128 | -0.156 | -0.189 | -0.181 | -0.122 | -0.079 | 1000 | | |
| (11) Dist_Train | -0.025 | -0.126 | 0.011 | -0.030 | -0.049 | -0.005 | -0.030 | 0.178 | 0.024 | -0.060 | 1000 | |
| (12) D_busstop | -0.087 | -0.045 | -0.006 | -0.051 | -0.028 | -0.043 | 0.031 | 0.055 | 0.006 | 0.045 | 0.059 | 1000 |

## Alternative regression specifications

results 150 meter

| Dependent: Rent per m2<br>VARIABLES | (1)<br>Baseline Model | (2)<br>City FE | (3)<br>Shopping District FE | (4)<br>Street FE | (5)<br>Interaction Large City | (6)<br>Interaction street FE |
|---|---|---|---|---|---|---|
| Log footfall | 0.241*** | 0.169*** | 0.198*** | 0.116*** | 0.152*** | 0.086* |
| | (0.017) | (0.023) | (0.025) | (0.041) | (0.029) | (0.046) |
| Log Footfall* large city | | | | | 0.109*** | 0.132 |
| | | | | | (0.036) | (0.097) |
| Log Size shop (m2) | -0.284*** | - 0.290*** | -0.286*** | - 0.358*** | -0.288*** | -0.358*** |
| | (0.022) | (0.016) | (0.017) | (0.017) | (0.017) | (0.017) |
| Distance to train (meter) | 0.000*** | 0.000** | -0.000** | 0.001*** | -0.000 | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Dummy busstop | -0.047 | 0.036 | 0.023 | -0.117** | 0.015 | -0.109** |
| | (0.029) | (0.030) | (0.031) | (0.047) | (0.031) | (0.047) |
| Log Number of Monument | 0.025*** | 0.036*** | 0.077*** | 0.070* | 0.055** | 0.065 |
| | (0.010) | (0.014) | (0.022) | (0.040) | (0.023) | (0.040) |
| Constant | 4.983*** | 5.410*** | 5.277*** | 5.735*** | 5.356*** | 5.708*** |
| | (0.195) | (0.224) | (0.256) | (0.422) | (0.257) | (0.422) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Observations | 1,576 | 1,576 | 1,576 | 1,576 | 1,576 | 1,576 |
| R-squared | 0.304 | 0.243 | 0.230 | 0.352 | 0.235 | 0.354 |
| Standard Control Variables | YES | YES | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES | YES | YES |
| City Fixed effects | NO | YES | NO | NO | NO | NO |
| Shopping district Fixed effects | NO | NO | YES | NO | YES | NO |
| Shopping street fixed effects | NO | NO | NO | YES | NO | YES |
| Number of Cities | | 64 | | | | |
| Number of Shoppingstreet | | | | 537 | | 537 |
| Number of Shoppingdistrict | | | 94 | | 94 | |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Results 50 meter

| Dependent: Rent per m2 | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Baseline Model | City FE | Shopping District FE | Street FE | Interaction Large City | Interaction street FE |
| Log Footfall | 0.286*** | 0.241*** | 0.245*** | 0.165** | 0.199*** | 0.096 |
| | (0.033) | (0.036) | (0.038) | (0.064) | (0.045) | (0.071) |
| Log Footfall * large city | | | | | 0.110* | 0.338** |
| | | | | | (0.058) | (0.154) |
| Log Size shop (m2) | -0.266*** | -0.278*** | -0.274*** | -0.327*** | -0.282*** | -0.329*** |
| | (0.038) | (0.030) | (0.030) | (0.032) | (0.031) | (0.032) |
| Distance to train (meter) | 0.000*** | 0.000* | -0.000 | 0.001*** | 0.000 | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Dummy busstop | 0.003 | 0.120** | 0.116** | 0.051 | 0.101* | 0.067 |
| | (0.052) | (0.052) | (0.053) | (0.086) | (0.054) | (0.086) |
| Log Number of Monument | 0.050*** | 0.029 | 0.043 | 0.105 | 0.012 | 0.100 |
| | (0.016) | (0.027) | (0.044) | (0.087) | (0.047) | (0.087) |
| Constant | 4.326*** | 4.636*** | 4.787*** | 4.187*** | 4.886*** | 3.916*** |
| | (0.358) | (0.369) | (0.417) | (0.806) | (0.419) | (0.810) |
| Observations | 488 | 488 | 488 | 488 | 488 | 488 |
| R-squared | 0.351 | 0.296 | 0.286 | 0.411 | 0.293 | 0.421 |
| Standard Control Variables | YES | YES | YES | YES | YES | YES |
| Time fixed effects | YES | YES | YES | YES | YES | YES |
| City Fixed effects | NO | YES | NO | NO | NO | NO |
| Shopping district Fixed effects | NO | NO | YES | NO | YES | NO |
| Shopping street fixed effects | NO | NO | NO | YES | NO | YES |
| Number of Cities | | 49 | | | | |
| Number of shoppingstreet | | | | 185 | | 185 |
| Number of shoppingdistrict | | | 66 | | 66 | |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1