Decreasing footfall rates during Covid-19: a catalyst on retail vacancy in the Netherlands?

Abstract

During 2020 and 2021, the Dutch government enforced restrictions to prevent the Covid-19 virus from spreading, which had considerable implications for the Dutch retail sector. The consequences of these restrictions were mainly visible in a significant decrease in footfall in Dutch shopping streets. Consequences of the significant decrease in footfall in Dutch shopping areas have yet to be investigated in existing literature, only a few studies have addressed this issue so far. Therefore, this study investigates the relationship between footfall and retail vacancy in shopping areas in the Netherlands, especially during Covid-19. A Logistic Regression Model (LRM) was performed on a large dataset containing property level data on 15,221 unique retail properties in 84 different shopping areas in the Netherlands. The results show that the chances that vacancy arises in the years 2015 – 2019 were lower, compared to 2020 – 2021, when footfall was significantly lower in Dutch shopping areas. Subsequently, the results from the LRM show a weakening association between footfall and retail vacancy during Covid-19, in the years 2020 and 2021. Which could mean that the consequences of Covid-19, especially the effects of the measures taken by the Dutch government, had an impact on the retail sector. A final discussion provides arguments for a more extensive analysis of this research topic to make thorough policy recommendations.

Key words: Retail, Vacancy, Footfall, Covid-19

Colophon

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CONTENTS

1. **INTRODUCTION**

1.1 Motivation

In recent years, Dutch shopping areas have faced many challenges in attracting shoppers, maintaining their attractiveness and preserving their vibrancy and economic sustainability. The growth of e-commerce and rapid transportation of goods has led to an increasing range of online shopping. As a result, the retail sector has proven to be highly volatile and sensitive to dynamic consumer demand and changing economic conditions (Rabobank, 2021). Retail vacancy is considered a key metric in measuring shopping areas' economic performance and liveliness (Talen & Park, 2021; Jacobs, 1961). Increasing retail store vacancies is often considered an issue directly related to an economic downturn, especially a diminishing value the retailer assigns to a retail property to make a profit (Balsas, 2004). Figure 1 shows the development of retail vacancy as a percentage of the total retail stock from shopping areas in the Netherlands. As shown in Figure 1, retail vacancy rates in Dutch shopping areas have increased significantly in 2020 and 2021.

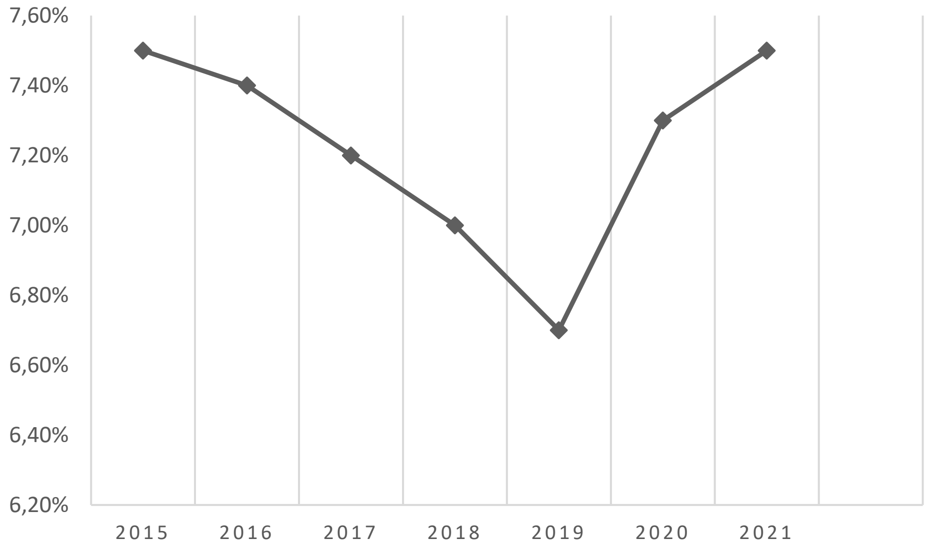

Figure 1. *Development vacancy in Dutch shopping areas (as % of total stock), January 2015 – 2021 (Locatus, 2022)*

With the arrival of Covid-19 in March 2020, the Dutch government was forced to take strict measures to prevent the spread of the virus. Shopping areas faced severe challenges as the number of daily visitors, or footfall, in shopping areas decreased substantially during lockdown periods. A chronological overview of the measures taken by the Dutch government during Covid-19 is presented in Appendix 1, in which a number of measures had major consequences for the Dutch retail sector. First, the advice to stay at home in the first partial lockdown in 2020 caused the first major decrease in footfall in shopping areas (Locatus. 2021). In addition, many retailers closed on their own initiative in fear of the virus. Second, during a strict lockdown in December 2020, retailers were officially obliged to close down for the first time, and allowed to open again at the beginning of February 2021. Third, the last lockdown was introduced at the end of December 2021, forcing retailers to close down again until January 2022 (RIVM, 2022; AD, 2020). To limit the economic damage for retailers during Covid-19, the Dutch government has provided financial support measures. These measures included, for example, allowances for fixed costs, deferral of tax payments on income and other measurements to compensate for possible loss of income (ABN Amro, 2021).

According to Locatus (2021), in December 2021, the vast majority of Dutch shopping areas have still not recovered to pre-Covid-19 levels in terms of footfall. Figure 2 shows the development of footfall as index figures with 2015 as the base year, in the 150 largest shopping areas in the Netherlands. Figure 2 shows that there has been a significant decrease of 43 per cent in footfall during Covid-19 in 2020 and 2021, compared to 2019 (Locatus, 2021). In addition, Research from ABN Amro (2021) shows that several retail branches benefited from the pandemic, but some had to cope with significant losses. Especially the fashion and shoe branch suffered from significant losses in turnover in 2020 (circa 20 per cent) and at the beginning of 2021 (circa 30 per cent), compared to 2019 (ING, 2022). According to ABN Amro (2021) and ING (2022), these branches rely heavily on footfall and physical customers in their stores, which is reflected in the decreased turnover.

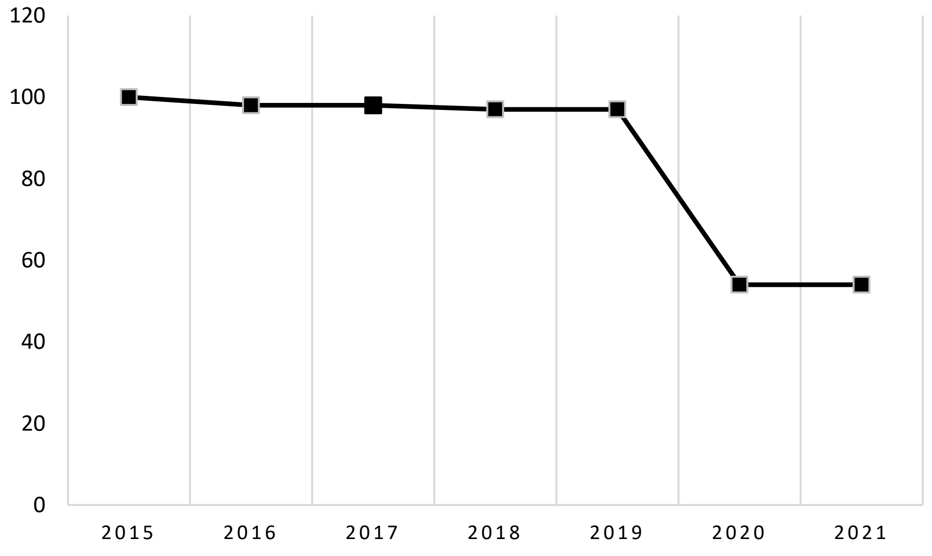

Figure 2. *Development footfall in Dutch shopping areas, 2015 – 2022 (2015=100) (Locatus, 2022)*

As a result of the Covid-19 measures put in place by the Dutch government (Appendix 1**)**, shopping behaviour has changed significantly, mainly reflected in footfall. Footfall is considered a reliable proxy to assess the performance of shopping areas and is often used as a core indicator of urban activity (Mumford et al., 2020; Enoch et al., 2021; Koster et al.,2021). However, only one study was found that examined a relationship between footfall and retail vacancy, which concluded a negative association between footfall and retail vacancy. Therefore, to better understand the dynamics of shopping areas and the impact of footfall on the economic performance of shopping areas in the Netherlands during Covid-19, this research focuses on the association between decreasing footfall during lockdowns and retail vacancy.

1.2 Academic relevance

The British Retail Consortium (2021) demonstrates that decreased footfall rates during Covid-19 had a multiplier effect on the rising vacancy rates in certain shopping areas in the United Kingdom, especially in the high streets. Retail vacancy is not only considered a problem for the property owner in the short term, but structural vacancy also has consequences for the shopping area in the long term. Increasing retail vacancy in shopping areas could lead to an economic downturn, decreasing the quality of the visual environment and decreasing the neighbourhood's social cohesion and safety (RTT, 2009). Koster et al. (2019) examines the relationship between footfall and retail vacancy by examining the effects of footfall on the probability of a shop becoming vacant. Their results show that footfall has a robust positive effect on rental income, meaning that the productivity of a retail firm depends heavily on local footfall. Moreover, retail properties in shopping areas with high footfall generate a higher rental income, in contrast to properties further away from the shopping area.

Similarly, using footfall to measure the performance of shopping areas has also been explored in research by Momford et al. (2019), and their research argues that footfall has excellent potential in identifying location attractiveness. In line with Momford et al. (2019), several studies examine the potential of assessing the performance and attractiveness of shopping areas by using footfall (Millington et al., 2015; Lugomer and Longley, 2018; Coca-Stefaniak, 2013). Other studies measure the relationship between footfall rates and the economic performance of city centres by mainly looking at retail rents as the dependent variable (Graham, 2017; Koster et al., 2019). These studies claim that decreased footfall rates strongly correlate with increased vacancy rates and the overall performance of the shopping centre.

Besides investigating the relationship between footfall and vacancy, this research contributes to the emerging literature examining the economic consequences of Covid-19, particularly the impact of Covid-19 restrictions put in place by governments. The association between Covid-19 restrictions and footfall has been examined by Koster et al. (2021). This paper examines the effect of several restrictions on footfall, such as lockdowns, face mask requirements and social distancing. Research from Koster et al. (2021) is one of the first attempts to examine the effects of footfall on town centres during lockdowns in the Netherlands. However, it does not consider the effects of decreased footfall on vacancy. Subsequently, the following studies examine the impact of Covid-19 on the retail sector in general, retail mix, and customer behaviour. Redda (2021) found significant differences in the impact of Covid-19 on South African retail sectors. At the same time, retailers in the pharmaceutical, medical, and food branches were least affected by Covid-19.On the other hand, the clothing, textile and footwear branches suffered high losses. Subsequently, Beckers et al. (2021) investigate the effects of Covid-19 on local retailers as a catalyst for e-commerce in Belgium. However, they concluded that it is still difficult to predict whether Covid-19 and the increased demand for e-retailers will fade away all non-essential retailers. Finally, Eger et al. (2021) further examine the effect of Covid-19 restrictions on consumer behaviour, discovering significant differences in shopping behaviour between generations.

Therefore, this study adds to the existing literature in two ways. First, this study contributes to recent studies about the economic consequences of Covid-19 on the retail sector. Second, existing literature (Koster et al., 2021; Graham, 2017; Mumford et al., 2020; Redda, E.H., 2021) examine the association between footfall and the economic performance of shopping centres, but vacancy is not often considered the primary variable of interest. In addition to the fact that there are generally few studies on the research topic, there are only a few case studies that have been performed in the Netherlands. Given the availability of a large amount of data for this analysis, this paper will be an excellent addition to fill the academic gap in the case of the Netherlands.

1.4 Research problem statement

This research aims to examine the relationship between footfall and retail vacancy in Dutch shopping areas and whether any differences in this association can be observed during Covid-19 (2020 – 2021). Based on the existing literature, the following research question is formulated:

"What is the association between decreasing footfall rates and retail store vacancy in shopping areas of the Netherlands during Covid-19 lockdown periods?"

Subsequently, the following sub-questions are formulated in order to examine the association between footfall and retail vacancy:

1. What are the main drivers of retail vacancy and what is the association between footfall and retail vacancy according to existing literature?
2. What is the association between footfall and retail store vacancy?
3. How has the association between footfall and retail store vacancy changed over the years 2015-2021?

1.5 Methodology and data

To answer the first sub-question, previous studies and relevant theories will be critically reviewed. First, it is important to understand the theoretical background behind retail vacancy and its determinants. Second, it is important to find out whether the existing literature can provide insights into a possible relationship between footfall and retail vacancy. After critically reviewing the existing literature, a large dataset will be used to analyse a possible relationship between footfall and retail store vacancy via a logistic regression model (LRM). Data is provided by retail research company Locatus and contains all the essential information regarding circa 15,000 unique retail properties in the Netherlands from 2015 to 2021. Unique to this analysis is that it uses property-level data and that each observation contains a unique object with associated location and property characteristics. The regression analyses measure the association between the independent variable footfall and the dependent variable retail vacancy. Finally, the last sub-question looks into the stability of the regression results and whether significant associations between variables can be established over the years 2015 – 2021. The contribution to existing literature is mainly made by the third, and also last, sub-question of this study, and elaborates on whether the decreasing footfall rates during Covid-19 catalysed retail vacancy in the Netherlands.

1.6 Outline paper

The remainder of this paper is structured as follows. Chapter 2 covers the theoretical background on the following concepts: retail vacancy and footfall. Chapter 3 explains the dataset used and the reliability and limitations of the data. Also, the operationalization of the dependent and independent variables, economic framework and the logistic regression model will be discussed. Subsequently, the results will be presented in chapter 4, which also includes a thorough discussion and a critical reflection on whether the results are in line with our expectations based on existing literature. Finally, a conclusion is presented in which the limitations of this study are discussed and where recommendations for future research are given.

2. THEORY

This chapter contains a theoretical framework which explains the most critical determinants of retail vacancy. Second, this chapter provides theoretical insights on footfall, the determinants of footfall and footfall in relationship to retail vacancy. Finally, two hypotheses are presented which will structure the empirical analysis, which is followed by the conceptual model.

2.1 Vacancy

Retail is of great importance attributing to the liveliness of a neighbourhood, mainly positioned along commercial shopping streets, often in combination with a shopping mall, and regularly considered the heart of a city centre (Talen & Park; 2021, Jacobs, 1961). A lively and well-performing shopping area often has benefits for its neighbourhood, supports local employment, and facilitates social connections (Talen & Park, 2021). Retail vacancy is considered one of the key metrics in determining the performance of a shopping area, and it is considered a visible indicator of how well a shopping area or shopping street is doing (Rhodes, 2014; Liang, 2006). One of the most important characteristics of vacancy is its duration, and a distinction can be made between frictional vacancy and long-term vacancy. However, a clear definition of the latter terms is difficult to find in the existing literature. Talen & Park (2021) argued that short-term or frictional vacancy generally turns over in a few months, which is considered a "transition time". On the other hand, long-term or structural vacancy, is mainly considered as properties being vacant for many months or even years. Primarily, structural vacancy is considered more impactful and problematic and an indicator of a less healthy real estate market (Tsolacos et al., 1993). Whereas frictional vacancy is considered a matter of transition and also considered to be necessary in order for a healthy real estate market to function properly (Talen & Park, 2021; Evers et al., 2014; Tsolacos et al., 1993).

The dynamics of retail vacancy

In order to understand retail vacancy, it is essential to look at theories that describe the dynamics of retail vacancy. City centres, shopping areas and shopping streets often resemble the structure of a monocentric city, which is characterized by having a pronounced centre where rents are the highest and are also characterized by the high number of pedestrians and shoppers. Retail firms are therefore attracted to areas with positive shopping externalities that attract customers. Simultaneously, vacancy rates are often increasing on the edges of monocentric cities, and these areas are more sensitive to economic conditions and adverse demand shocks, such as an economic crisis (Teulings et al., 2017). In addition, Teulings et al. (2017) argue that retail located further away from a city centre is also considered less profitable and that rents are often higher and retail vacancies lower near the city centre. DiPasquale and Wheaton (1992) also consider retail markets to be primarily local because the performance and activity of a retail centre are mainly determined by its local demography and economy. This means that local employment and market demand are crucial determinants of the performance of a shopping centre.

The supply and demand for retail space are essential in understanding how retail rents are set and how retail vacancy arises. A critical theory to explain these market dynamics is the four quadrants model by DiPasquale and Wheaton (1993). This model is a conceptual framework for commercial real estate markets and helps understand the interrelation between real estate users and the asset market. Moreover, it helps explain how macroeconomic drivers affect real estate markets. The Four Quadrant Model (4Q-model) is visualized in Figure 3.

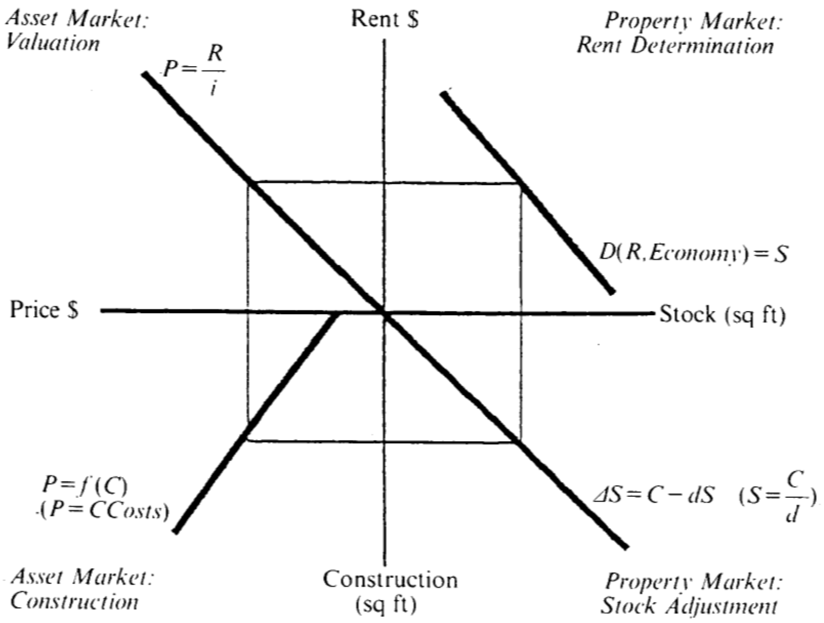

Figure 3. *Real Estate: The Property and Asset Markets (DiPasquale & Wheaton, 1992)*

The 4Q model is subdivided into two markets; the right-hand quadrants represent the property market for the use of space, and the left-hand quadrants represent the asset market for real estate ownership. The Nort-East quadrant (Q1) is where commercial rents are determined. In equilibrium, the demand function for space is equal to the stock of space. Rents are determined by taking a level of stock on the horizontal axis up to the demand curve. The North-West quadrant (Q2) represents the first part of the asset market and consists of two axes: rent and price (per unit of space). The ratio between these indicators results in a capitalization rate (or yield). The yield is the current yield demanded by investors to hold their real estate assets. Given the price of the real estate assets in the North-West quadrant and the costs of new construction, the asset market's South-West quadrant (Q3) determines the construction of new real estate assets. Finally, the South-East quadrant (Q4) represents the total stock of real estate. Where the change in stock in a given period equals new construction minus depreciation of the existing stock, to understand the emergence of retail vacancy according to the 4Q model, we start with several shocks that can change the supply or demand for retail real estate. Benjamin et al. (1998) describe the following influences: changes in retail sales, rental prices, land-use regulation, land availability, and the cost of capital. Also, Talen & Park (2021) distinguish two interrelated dynamics that determine retail vacancy; changes in the retailing industry and drastic demographic changes. The first dynamic mainly entails long-term structural changes in the retail sector, linked to changing consumer behaviour, technical innovation and government law and regulations. The second dynamic influencing retail vacancy is changing demography. Demography trends include the lack of population thresholds needed to support retail or the ageing population in neighbourhoods (Talen & Park, 2021). Similar trends are mentioned by Kok (2021), such as individualization, gender shifts, health and mobility. Finally, Liang (2006) argues that higher demand uncertainty and search frictions induce increasing vacancy rates.

We can use the 4Q model to understand the dynamics in supply and demand for retail space when considering the possible trends mentioned in the previous section. The 4Q model mainly discusses long-term real estate market adjustments, where all quadrants move towards equilibrium. The latter makes it more difficult to explain how vacancy could arise in the short term. Following the four quadrants, counterclockwise, vacancy could arise as follows, starting in Q1. User demand is stimulated through a particular demand shock, which increases the demand for retail properties in Q1, immediately stimulating rent increase.

Consequently, asset prices will be driven up in Q2, which increases the value for investors and constructors to develop or redevelop new retail properties, as the asset value is higher than the replacement value (Q3). Q4 converts the annual flow of new construction into a long-run stock of real estate space. However, adding too many properties to the market could lead to a mismatch between supply and demand, leading to vacancy. In essence, according to Colwell (2002), the 4Q model always assumes frictional vacancy, which is developed in the South-East quadrant. When new assets are added to the existing stock, it takes time to get them occupied. However, the latter is not considered problematic for the real estate market as it concerns frictional vacancy.

2.2 Footfall

Footfall is defined as the number of walking visitors passing a shop or walking up and down shopping streets, regardless of their reasoning (Koster et al., 2019; Coca-Stefaniak, 2013; Graham, 2017). Besides vacancy, footfall is often considered a key metric in assessing the performance of a shopping area or street. In the same way, Parker et al. (2016) argue that footfall is the most influential metric in assessing the vitality of shopping areas, according to consulting 22 experts in real estate. According to the literature, footfall is often linked to the attractiveness of a shopping area and is often used as an indicator in classifying potential purchasing power (Mumford et al., 2020; Coca-Stefaniak, 2013;

Philp et al., 2020; Koster et al., 2019). Moreover, footfall is considered a measure of consumer behaviour, shopping experience, and day-to-day patterns of pedestrians (Lugomer & Longley, 2018).Conversely, footfall is not only considered a key metric in assessing the attractiveness of shopping areas in general. However, Millington et al. (2015) also found that footfall can be used as a proxy for assessing the attractiveness of an area regarding social and communal functions. Several characteristics affect footfall, which can be distinguished by macro- and micro-level characteristics. According to Brown (1993), micro characteristics encompass the impact of the immediate location of the shopping area, such as retail mix, the physical appearance of the shopping centre and general accessibility. On the other hand, macro characteristics are broader trends such as economic or demographic changes and weather conditions (Dolega et al., 2016).

A summarized analysis of all determinants of footfall can be found in research by Philp et al. (2020). This paper distinguishes between three different groups of determinants, functional, morphological and other, which can be subdivided into different spatial and temporal scales. Functional determinants of footfall comprise the function of the shopping area. For example, retail mix or the presence of anchor stores. Research has shown that an extensive retail mix can significantly boost footfall (Millington et al., 2015). Moreover, if the shopping area also has a large concentration of businesses and employers, this could significantly benefit footfall. The second group of determinants entails factors concerning morphology (the shape of the shopping area) and general accessibility. According to Philp et al. (2020), general accessibility is determined by many factors, such as security, network connectivity to other streets or shopping areas, public transport or car parks, and walkability. Especially walkability is considered one of the main determinants of accessibility, according to Philp et al. (2020). Furthermore, the morphology of the shopping area determines the degree of walkability. A shopping area characterized by good morphology consists of wide and open streets, street lightning or a pleasant physical appearance of the built environment (Erath et al., 2017). Finally, the last factor contributing to footfall is weather conditions. However, as Makkar (2020) notes, weather conditions are only considered a short-term influence on footfall.

2.3 Footfall versus Vacancy

The previous sections provided theoretical background on vacancy and footfall. However, this paper aims to investigate the association between footfall and vacancy. Few studies examine the association between footfall and vacancy, and both are considered performance metrics several times (Rhodes & Brian, 2014; Koster et al., 2019; Philp et al., 2021). In addition, previous studies also show that the two factors often go hand in hand when assessing a shopping area's performance. For example, Enoch (2021) stated that, while assessing shopping streets in the United Kingdom, vacancy rates were at their highest when footfall was at its lowest during Covid-19, but examining a possible association has only been performed by Koster et al. (2019). Continuing on the latter, given that theory on the association between footfall and retail vacancy is very scarce, it might be interesting to look at this more broadly from urban theories (Alonso, 1964; Teulings et al., 2017; DiPasquale & Wheaton). Therefore, based on the theories mentioned in this chapter, when there are high levels of footfall in shopping areas, vacancy is expected to be lower. On the other hand, one might also expect that when footfall levels are significantly lower, this could be reflected in retail vacancy. Teulings et al. (2017) indirectly explain that shopping areas with high vitality and footfall often experience lower vacancy and higher rents. Teulings et al. (2017) already described that some shopping areas might be more sensitive to shocks. Subsequently, the Dutch government has implemented various financial support measures during Covid-19; these measures have been implemented during extreme market conditions (ANP, 2021; RTL Nieuws, 2022). It could be that these measures have disrupted the market mechanism, and that the relationship between footfall and retail vacancy is also affected during 2020 and 2021.

2.4 Hypotheses

The following hypotheses are formulated based on the theories explained in the previous sections. The hypotheses are fundamental to the empirical analysis in this study. The first hypothesis follows studies examining the association between footfall and vacancy. Especially studies where both footfall and retail vacancy are considered metrics in assessing the performance of shopping areas (Rhodes & Brian, 2014; Koster et al., 2019; Philp et al., 2021; Enoch et al., 2021).

H1: There is a negative association between footfall and retail vacancy

The second hypothesis is a non-directional hypothesis, meaning it is not directly related to the existing literature because the second hypothesis explores whether a difference can be observed during Covid-19 (2020/2021).

H2: The association between footfall and retail vacancy changes over time

Based on the hypotheses and theories set out in this chapter, a conceptual model has been drafted in figure 4.

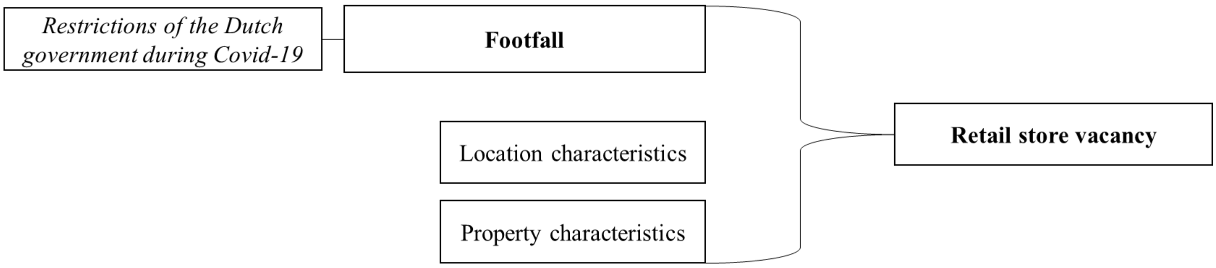

Figure 4. *Conceptual model*

3. DATA & METHODOLOGY

This chapter introduces the dataset used in this study and the research methodology. The first section describes the dataset and the data-selection process. The second section captures the limitations of the data. Subsequently, the third section discusses the operationalization of the data and presents the descriptive statistics of the dependent and independent variables. Finally, the empirical model and regression equation are presented, including a description of the sensitivity analyses.

3.1 Dataset

The primary goal of this study is to examine the relationship between footfall and retail store vacancy in Dutch shopping areas. Retail research company Locatus has provided the dataset used for this study containing all the necessary information for the statistical analysis. Locatus gathers data on all shops, stores, and consumer-orientated service providers in Benelux (Locatus, 2022a). Their database provides property-level information, such as shop profile, retail floor space, retail sector, footfall, et cetera, and is mainly collected via fieldwork[1]. All the data necessary for this study were obtained via an internship at Locatus and retrieved from Tableau, PowerBI and Locatus' online environment, and were finally merged into one large dataset.

The dataset contains all the necessary information to compile the dependent and independent variables. The unit of analysis is the independent retail property. The dataset shows whether the retail property was vacant, yes or no, from 2015 to 2021 and its property and location characteristics. Locatus only observes each retail property once a year and is registered as vacant if it is reasonably expected that the (vacant) property will house a retail outlet, catering industry, or consumer-oriented services that will return in the (near) future (Locatus, 2022a).Other criteria in classifying a vacant property are the following. First, within a shopping area, the building was used before for retail purposes and is empty, or the property is no longer in use as a shop or catering industry at that time but is on the property, indicating that it is for sale or rent (as a point of sale). Second, outside shopping areas, both criteria must apply to a property (Locatus, 2022a). The dataset also consists of annual footfall counts from 2015 to 2021. Data on vacancy, footfall and other property and location

[1] Locatus uses the following definition for physical retail properties: *"Locatus' database only incorporates retail activities on a fixed location. Furthermore, it must be an indoor space reasonably accessible to consumers. 'Reasonably accessible' can mean that an entrance fee is charged. Therefore, retail premises where entry is granted only to an exclusive target group cannot be considered reasonably accessible. A distinction in the database was made between retail units and shop-in-shop. A retail unit means a building with an address in which consumer-orientated services are engaged. A shop-in-shop is a physical space that is part of a retail unit with the same address but that is autonomous. This space is usually physically separable and only accessible via the 'parent unit. There will always be a separate checkout for any activity occurring. In principle, the retail floor space will be measured separately. Locatus only includes and considers properties in their database in which a permanent economic activity is established, to sell goods or services to passing consumers in a shopping area, are regarded as retail properties."* (Locatus, 2022a)

characteristics are collected through periodic visits to shopping areas in the Netherlands by field workers from Locatus. The method for collecting these data is described later in this chapter.

Shopping areas

For this study, several steps were taken in selecting the shopping areas[2]. Since it is essential to look at a possible catalytic effect of decreasing footfall during Covid-19 on retail store vacancy, only shopping areas must be included where footfall counts by Locatus have been consistent throughout the years, and most importantly during Covid-19. Therefore, the first criterion in selecting the shopping areas for this study was the data availability per shopping area. Second, only shopping areas were included with at least a footfall of 5000 per counting point per day. The latter criterion was chosen to exclude shopping areas that were too small and did not have sufficient data on retail properties over 2015-2021. Before selection, the dataset consisted of 150 shopping areas and 54,667 unique retail properties. After selection, 84 shopping areas and 15,221 retail properties remained. A list of all included areas can be found in Appendix 2.

There is a distinction to be made between shopping areas where the last footfall count took place in the spring of 2021 (Figure 5a) or the autumn of 2021 (Figure 5b).Having a difference between groups is essential in this study because, during the spring of 2021, the Netherlands was still in lockdown, but there were no longer any Covid-19 restrictions in the autumn. Because people had less freedom of movement during the Covid-19 restrictions in force, this is also reflected in differences in footfall between these two groups in the dataset. For example, where the mean of footfall in spring 2021 was 12,236 passers-by per day, a slight increase was observed in autumn 2021, where the mean of footfall was 12,427 passers-by per day.

[2] Locatus defines a shopping area as follows: *"A shopping area is considered a concentration of five or more retail outlets, no matter the kind of retail or the size. Also, a concentration with at least three retail outlets, including a supermarket of at least 500 square meters, is considered a shopping area. Interdependence of the stores is also a requirement"* (Locatus, 2022).

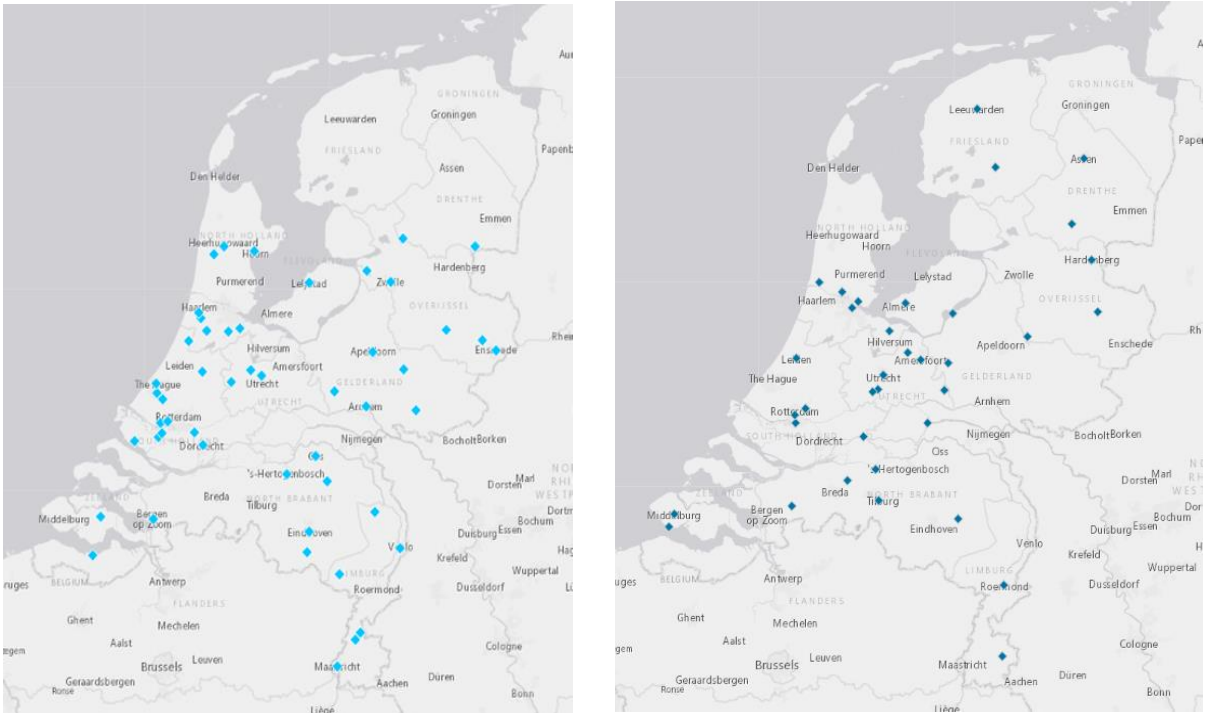

Figure 5a & 5b*: Shopping areas with last count in spring 2021, total 37 (5a. left Figure) and shopping areas with last count in autumn 2021, total 48 (5b. right Figure) (source: Locatus, 2022)*

Footfall

Locatus has manually been tracking footfall data for over twenty years using the same method used in 150 shopping centres in the Netherlands. Footfall in a shopping area is counted at a rotating schedule where different points in the shopping area are covered. The counting points are set at the busiest traffic points in shopping areas to capture the full shopping potential of the shopping street. Footfall counts always occur on so-called “representative Saturdays” during the year, meaning at the end of March or the beginning of April, or at the end of September or October (Locatus, 2022b). Each counting point is linked to several retail properties. Therefore, footfall is explicitly determined for each retail property. Based on the intensity of footfall, an estimate is then made of the footfall number per time frame in a particular area (Locatus, 2022b). The surveyors who perform the footfall counts are very specific and consistent; they include everyone who passes the counting position from both directions. However, cyclists, employees of retail and restaurants, children in pushchairs, security guards and anyone other who is not considered a shopper are excluded from the counts (Locatus, 2022b).

Because of the consistency of the counts every year, it is very convenient to use the footfall data from Locatus to compare the performance of several shopping centres over multiple years. Other studies use footfall data collected by Wi-Fi sensors that track mobile phones carried by pedestrians in city centres

(Koster et al., 2021; Philp et al., 2021; Lugomer et al., 2017). Especially in the retail analytics sector, Wi-Fi tracking is a widely used metric to monitor footfall (Miorandi, 2017). However, this method raises serious privacy concerns (Spiess, 2021; DPA, 2021). In recent years there has been an ongoing debate about using these data to measure footfall, especially during Covid-19 (Ahmad & Chauhan, 2020; Buchanan et al., 2020). In 2021, the Dutch Data Protection Authority (DPA, 2021) argued that Wi-Fi-tracking violates people's privacy and therefore is illegal to measure footfall (Van Schaik, 2021). Moreover, it is alsoquestionable whether Wi-Fi tracking is reliable in terms of accuracy.

The so-called MAC randomization is a process that hides a mobile device's exact identity to guarantee the privacy of Wi-Fi networks (CenturyLink, 2022). Philp et al. (2021) mention that measuring footfall with MAC addresses via mobile devices cannot filter out repeated counts because MAC randomization generates random addresses for Wi-Fi Networks, creating multiple devices when there is only one device should be included in the footfall count. The previous discussion explains the controversy in using Wi-Fi tracking to measure footfall. Therefore, the data from Locatus is considered more accurate due to the lack of technical issues that arise from counting manually. Moreover, manual counts could be considered a more ethical approach regarding privacy issues[3].

On the next page, Figure 6 shows an example of the distribution of footfall counting points in The Nine Streets in Amsterdam[4]. Figure 6 shows that multiple counting points are divided over this area. Figure 7 shows the distribution of footfall counting points in the city centre of Coevorden. This map is another example of how counting points are distributed over a shopping area in a different, more regional shopping area compared to The Nine Streets in Amsterdam.

[3] During this research, the guidelines for conducting ethically responsible research, which were drawn up by the Association of Universities in the Netherlands (VSNU), were taken into account as much as possible. A full representation of all guidelines have been drawn up in the Netherlands Code of Conduct for Research Integrity (2018).

[4] The Nine Streets in Amsterdam: Gasthuismolensteeg, Hartenstraat, Reestraat, Berenstraat, Wolvenstraat, Oude Spiegelstraat, Wijde Heisteeg, Huidenstraat, Runstraat.

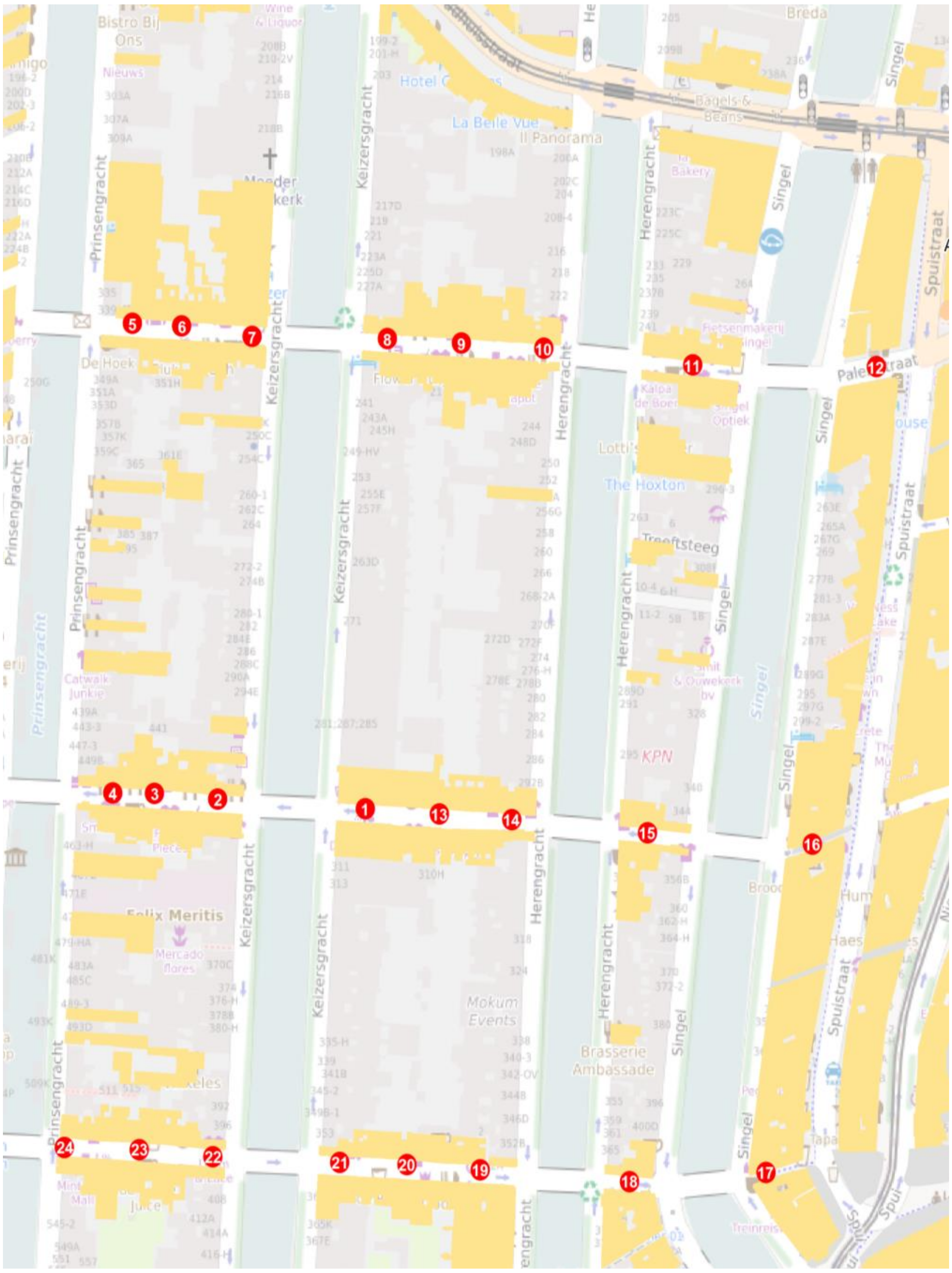

Figure 6*: Example of distribution of counting points for footfall – The Nine Streets, Amsterdam (Source: Locatus, 2022)*

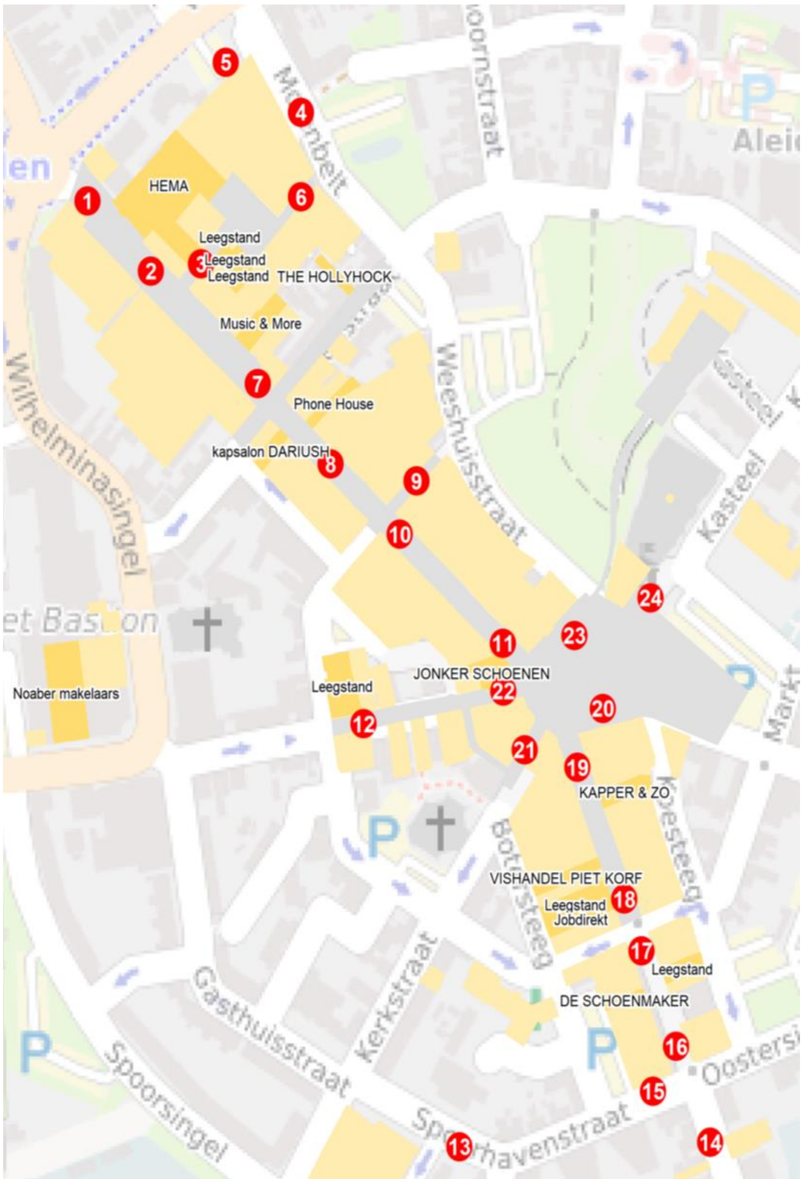

Figure 7*: Example of distribution of counting points for footfall – Coevorden (Source: Locatus, 2022)*

<u>3.2 Reliability and limitations data</u>

Locatus ensures fieldworkers and footfall surveyors consistently check and monitor shopping areas and the associated retail properties. Their fieldwork and research methods have also remained persistent over the years, resulting in solid datasets containing extensive information about shopping areas in the Netherlands. Locatus visits all shopping areas periodically. However, not all shopping areas are visited simultaneously, which could lead to some delays in the data. The latter is essential when examining the relationship between footfall and whether a property is vacant or occupied at a particular moment. The delay in visits of shopping areas could lead to the following bias for this study. First, observing structural and non-structural vacancy in retail properties is more complicated because the properties are only observed once per year. Therefore, the dataset does not distinguish between different types of vacancies. The type of vacancy (frictional or structural) could tell us more about the performance of the shopping centre, which we need help to capture in this study. Second, not observing different types of retail vacancies could lead to inconsistencies in interpreting the results because there are different economic drivers behind different types of vacancies. Third, there are sometimes properties that could be registered as vacant but sometimes are not. The latter refers to the concept of financial vacancy. *Financial vacancy* is a term used for rented properties but not used. For example, a tenant with a specific policy or, for whatever reason, decides to rent the property but not use it. This type of vacancy is complicated to observe given that a building is not used for its current function, namely retail (NVB, 2003). However, the chance of this occurring is minimal and, therefore, negligible.

Another relevant limitation is that the counting date for counting footfall deviates from the periodic visits where property characteristics are monitored, such as vacancy. Unfortunately, no clear pattern or schedule is observed in the dataset on how these periodic visits differ. I have solved the latter as much as possible by matching the counting date for footfall and the fieldwork date for all properties in the dataset. Properties where these two dates were too far apart from each other were therefore left out in the analysis. The difference in periodic visits could lead to a bias regarding a mismatch in data collection. In contrast, footfall is measured on a different day than retail vacancy and is difficult to compare.

The last caveat to mention concerning the footfall data is that it is a proxy over an extended period; it is not data monitored on a daily or weekly basis and therefore remains an estimate, in contrast to similar studies that used Wi-Fi-tracking to measure footfall (Koster et al., 2021; Philp et al., 2021; Lugomer et al., 2017), where footfall data was captured daily. Again, the previous section explains the ethical considerations and privacy issues and why these data are considered less reliable. Nevertheless, the data used in this study is regarded as some of the best data available on retail characteristics, vacancy and footfall regarding reliability, consistency and quality.

3.3 Operationalization data & descriptive statistics

For this analysis, our dependent variable is retail store vacancy, and a set of independent variables include footfall, store size, year fixed effects, location fixed effects and property characteristics. All variables are computed based on data provided by Locatus. Locatus indicates vacancy at a binary level during the periodic visits, whether the property is vacant (1 = Yes), or whether the property is not vacant (0 = No)[5]. Because the dependent variable is measured on a binary level, the coefficients in the regression models are estimated via a Logistic Regression Model (or LRM). Where the primary explanatory variable of interest, footfall, is measured as a ratio variable. However, computing a

[5] As mentioned before, no distinction has been made between frictional, structural or long-term vacancy in the dataset. It is measured as vacant or occupied at the field work date, regardless of the duration. Because apparently, it is impossible to capture this when periodic visits only take place once a year. For example, capturing frictional or financial vacancy can only be captured when there is information on lease contracts and tenants.

histogram of the variable footfall showed that the variable was heavily skewed (Appendix 3). Therefore, footfall was transformed into a logarithm of footfall (ln_footfall) to get a more normal distribution. The same accounts for store size, which also appeared to be heavily skewed and was transformed into a logarithm of store size (ln_storesize).

A pronounced concern could be potential endogeneity problems, as discussed by Koster et al. (2019). There might be an effect of vacancy rates of retail properties on the footfall these properties generate. Unobserved location or property characteristics could be highly correlated with footfall. To reduce the risk of endogeneity, fixed effects were included in the model following models from Koster et al. (2019;2021). Property, location and year fixed effects were added to minimize possible endogeneity (Hill et al., 2021). Location fixed effects consist of dummies for each of the 84 shopping districts, dummies per region and shopping area type. Property characteristics include construction year dummies, categorized as <1650, 1650-1750, 1750-1850, 1850-1950, 1950-1980, 1980-2000, >2000 and 1005. The year fixed effects to control for changes of the retail property from 2015 to 2021.

In order to include all relevant variables in the analysis, correlations between the variables were explored. The correlation matrix can be found in Appendix 4. correlation between variables is measured on a scale from -1 to +1, with -1 being a strong negative correlation and +1 being a strong positive correlation (Brooks & Tsolacos, 2010). The primary independent variable of interest, footfall, does not appear to have a strong correlation with retail vacancy (-0.119) or store size (-0.025), which causes no reason for concern. However, including some location variables causes multicollinearity between the independent variables, which means that some independent variables correlate with each other (Brooks & Tsocalos, 2010). Therefore, the model excluded the dummies for region and shopping area type.

Descriptive statistics

This section presents the main descriptive statistics for all the variables included in the analysis, where the primary dependent variable of interest is store vacancy. Table 1 summarises all the descriptive statistics from our dataset, including the mean, standard deviation, minimum and maximum value per variable. In total, we have 106,195 observations over 2015 to 2021, which contain 15,221 unique retail properties (Unit IDs) spread over 84 shopping areas in the Netherlands. To get a better understanding of the characteristics of the properties, the data was also split into two samples; properties that were vacant and properties that were occupied from 2015 to 2021.

In general, Footfall numbers vary between 400 and 73,100 per day, with a mean daily footfall of 13,853 and a standard deviation of 9,668. Store size varies significantly between retail properties, ranging from 10 to 63425 square meters. Most retail properties lie around the mean of 366 square meters in store size. When looking at the differences between the retail properties that have been observed as vacant or occupied over the years, the following thing stands out; a significant difference in footfall can be observed between the two samples, where the vacant properties experienced footfall with a mean of 10,680 per day, in contrast to occupied properties which experienced a mean of 14,157 per day. Nevertheless, comparing vacant and occupied properties should be done with care. In this study, footfall and retail vacancy are observed on property level, where each observation is a unique property with unique property characteristics. Therefore, comparing occupied and vacant properties without considering other property characteristics will not tell the whole story. However, in line with our expectations, the descriptive statistics already show that less footfall is observed with vacant properties.

The ratio variable construction year is subdivided into categories, and the division of the categories can be seen in the table below. However, it is important to mention the following regarding the variable construction year. Category 1005 in table 1 is a classification used by the Basic Building Administration (BAG) in the Netherlands for buildings of which the year of construction is unknown. Therefore, this category contains properties we do not know the construction year. A limitation should also be mentioned in using the construction year of the BAG. The construction year of a retail property is used as a specific point in this analysis. However, it excludes extensive scale renovations, such as the renovation of Hoog Catharijne in the city centre of Utrecht, which has transformed significantly and could be considered an entirely new shopping area. This might be a limitation because the construction year correlates with location characteristics. However, this only accounts for a minor part of the analysis's retail properties; therefore, the effect should be considered negligible.

Table 1 – Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Vacancy	106,195	.087	.282	0	1
Vacant	*9,244*				
Occupied	*96,951*				
Footfall	106,195	13853.278	9668.295	400	73100
Vacant	*9,244*	*10680.1*	*7042.751*	*400*	*73100*
Occupied	*96,951*	*14156.95*	*9829.159*	*400*	*73100*
Store size	106,195	366.931	1245.023	10	63425
Vacant	*9,244*	*302.013*	*753.726*	*10*	*16247*
Occupied	*96,951*	*373.129*	*1281.988*	*10*	*63425*
Year	106,195	2017.997	2.001	2015	2021
Shopping district	106,195	41.44	25.602	1	84
Region					
Friesland	2,380	.022	.148	0	1
Drenthe	10,067	.095	.293	0	1
Overijssel	6,305	.059	.236	0	1
Gelderland	9,098	.086	.28	0	1
Flevoland	1,162	.011	.104	0	1

Noord-Holland	19,791	.186	.389	0	1
Zuid-Holland	20,796	.196	.397	0	1
Utrecht	10,152	.096	.294	0	1
Noord-Brabant	13,792	.13	.336	0	1
Zeeland	3,444	.032	.177	0	1
Limburg	13,447	.127	.333	0	1
Shopping area type					
Inner city	39,486	.372	.483	0	1
Large scale concentration	896	.008	.091	0	1
Main shopping area	60,557	.57	.495	0	1
Large-scale core retail area	2,267	.021	.145	0	1
Down town area	2,989	.028	.165	0	1
Construction year					
<1650	106,195	.072	.258	0	1
1650> <1750	106,195	.036	.187	0	1
1750> <1850	106,195	.06	.237	0	1
1850> <1900	106,195	.112	.315	0	1
1900> <1950	106,195	.278	.448	0	1
1950> <1980	106,195	.207	.405	0	1
1980> <2000	106,195	.157	.364	0	1
>2000	106,195	.079	.269	0	1
1005 (BAG)	106,195	.044	.205	0	1

The variables region and shopping area type were still included in the descriptive statistics, although these variables were left out due to multicollinearity. The variables show how the observation in the dataset is divided over different locations. For example, this dataset does not cover any shopping area in Groningen. The reason for this is that the last count in Groningen took place before Covid-19, and therefore there are no footfall data on shopping areas in Groningen. For this reason, we omitted this region from descriptive statistics simply due to missing data on this region.

Based on the different characteristics of the shopping area, a distinction can be made between different shopping area types. The distribution of the classification by type of shopping area per retail property is listed in table 2. According to Locatus (2022), the shopping areas are classified as follows. First, a city district centre is always added to a city centre or primary retail centre. For example, in this dataset, Utrecht Overvecht, Amsterdam Boven ‘t IJ and Buitenmere near Almere are considered city centre districts. Second, a sizeable subregional centre is a town or city's most significant retail area. This pertains to centres with 50 to 100 shops. Examples of large subregional centres are the centre of Coevorden, Nieuwegein and Soest. Third, the majority of shopping areas in this dataset are considered regional centres. A regional centre is the most significant retail area of a town or a city and contains 100 to 400 shops. Examples of regional centres in this dataset are the centre of Doetinchem, Amstelveen and Harderwijk. Fourth, a large number of the shopping areas are referred to as the city centre. This pertains to the seventeen most important retail areas in the Netherlands. Examples of city centres in this dataset are city centres of Amsterdam, Utrecht, Haarlem and Rotterdam. The final classification is big box retail parks. These are concentrations of five or more shops with an average retail floor space minimum of 500 square meters per shop. Furthermore, fifty per cent of the shops must be targeted at furniture and DIY. An example of big box retail parks in this dataset is Rotterdam Alexandrium. This dataset contains property data on 15,221 unique properties or Unit ID's. The number of retail properties per shopping area type is also shown in table 2**,** showing that the majority of all retail properties are located in regional centres and city centres.

Table 2: *Classification of shopping areas*

UNIT ID'S	Total	15,221
SHOPPING AREAS	Total	84
TYPE OF SHOPPING AREA	**CLASSIFICATION**	**No. UNIT ID'S**
City District Centre	>50 shops*	431
Subregional Centre Large	50-100 shops	324
Regional Centre	100-400 shops	8683
City Centre	>400 shops	5714
Big Box Retail Park	Retail parks	128

It should be mentioned that there might be a limitation in the analysis by including retail parks, including shopping malls. It often occurs that real estate owners charge lower rents in shopping malls to retail firms that generate a high footfall, mainly anchor stores that attract many customers. Therefore, considering retail located in shopping malls (e.g. hoog Catharijne, Rotterdam Alexandrium) could lead to bias in the analysis because the rents are determined differently (Brueckner, 1993). The latter could affect how vacancy arises in shopping malls, in contrast to vacancy in "normal" shopping areas included in the analysis. However, similarly to category 1005 in the construction year, this effect is expected to be a minor caveat due to the significant size of the dataset.

3.4 Empirical model

The previous section extensively explained the data selection method and operationalization of the variables. We aim to measure the relationship between retail vacancy and footfall in shopping areas in the Netherlands. In order to test the first hypothesis, multiple regression analyses are used to estimate the association between a dependent variable and a set of independent variables. The model in this study consists of our variable of interest, vacancy, that we aim to predict with a set of explanatory variables based on the theoretical framework, where the primary explanatory variable of interest is footfall. The suitable regression model to perform the analysis is a discrete choice model where the dependent variable only consists of a limited amount of options. The latter can be summarized in an empirical model that explores the relationship between the dependent and independent variables:

$$Vacancy\ (1 = yes)$$
$$= \beta_0 + \beta_1(\ln\_footfall_i) + \beta_2(\ln\_store\_size_i) + \beta_3(property\ characteristics_k)$$
$$+ \beta_4(location\ fixed\ effects) + \beta_5(year\ fixed\ effects) + \beta_6(ln_{footfall}*_{year}\ i) + \epsilon_i$$

Our dependent variable vacancy is a binary variable with only two outcomes (0 = not vacant, 1 = vacant). Subsequently, a set of independent variables is defined as follows. Firstly, *ln_footfall* is our primary independent variable of interest as the natural logarithm of footfall.
Secondly, *ln_store_size* refers to the natural logarithm of store size, measured per square meter. Thirdly, another key variable of interest is added to the model, which explores the interaction of the natural logarithm of footfall against the years in the analyses. This interaction variable examines whether the relationship between footfall and vacancy depends on the year (2015 – 2021). Finally, the control variable property characteristics, location fixed effects and year fixed effects were added to the empirical model. The ϵ_i is the error term assuming a logistic distribution.

3.5 Model building

For this analysis, the decision has been made to work with a balanced dataset, meaning a dataset that contains all variables observed in a particular time frame. In this study, the time frame concerned is from 2015 to 2021. The reason for choosing a balanced dataset is that balanced data, on average, generates higher accuracy models, especially for panel data, which we are dealing with in this analysis (Baltagi, 2005). Following Koster et al. (2019), the strategy used to build the model is a step-wise method. Starting with a baseline model and gradually adding independent variables to the model. Independent variables are added based on the theory described in this study. A step-wise method is convenient for analysing how coefficients change and better understanding the effects of the independent variables on the dependent variable. A sufficiently working model contains all the possible independent variables that explain the dependent variable vacancy.

4. RESULTS

In this chapter, the findings of the baseline model will first be discussed where I focus on the between footfall and retail vacancy. In the second part of this chapter, extensions of the model will be discussed, and finally, the sensitivity analyses are presented.

4.1 Baseline model

Table 3 reports the results for a retail property being vacant and how it is associated with footfall using a Logistic Regression Model (LRM). The specification in column (1) is a naïve specification of the dummy variable vacancy, meaning that I regress the dependent variable with the primary independent variable without considering other independent variables and the fixed effects. The coefficient for *log footfall* appears to be significantly different from zero at the 99% confidence level. Moreover, the coefficient shows a negative association with retail vacancy, which aligns with research from Koster et al. (2019), who indicated a similar association. Therefore, the association in column (1) needs to be interpreted as a 1% increase in footfall decreases the odds of a retail property becoming vacant by a factor of = 1.00692 times. Another way of explaining this is if footfall increases by 1%, the odds ratio of a retail property becoming vacant decreases by 0.692%, ceteris paribus. Alternatively, if footfall increases by 10%, the odds ratio of a retail property becoming vacant decreases by 6.92%.

The specification in column (1) illustrates that the size effect aligns with existing literature. The following section presents the other model specifications (columns 2 – 6) in which control variables and fixed effects have been added. Spatial and time-fixed effects have been included to control for possible omitted variable bias (Livy and Klaiber, 2016). Following Koster et al. (2019), the control variables *store size* and *construction year* (property characteristics) have also been incorporated into the regression models.

Table 3 – logistic regression output

Footfall and Vacancy

(Dependent variable: shop is vacant)

	Baseline	*Storesize*	*Year fixed effects*	*Location fixed effects*	*Property Characteristics*	*Interaction variable*
	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	Logit	Logit	Logit	Logit	Logit
Footfall *(log)*	-0.692***	-0.686***	-0.633***	-0.406***	-0.405***	-0.445***
	(0.018)	(0.018)	(0.018)	(0.022)	(0.022)	(0.021)
Store size *(log)*		-0.04***	-0.045***	-0.091***	-0.097***	-0.097***
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

Interaction (Footfall*Year)					*2016*	0.009** (0.005)
					2017	0.021*** (0.005)
					2018	0.024*** (0.005)
					2019	0.036*** (0.005)
					2020	0.061*** (0.005)
					2021	0.074*** (0.005)
Year fixed effects	No	No	Yes	Yes	Yes	Yes
Location fixed effects	No	No	No	Yes	Yes	Yes
Property characteristics	No	No	No	No	Yes	Yes
No. obs.	106,195	106,195	106,195	106,195	106,195	106,195
R^2	0.025	0.025	0.030	0.061	0.063	0.063

*Notes: Footfall is measured as the number of passing-by shoppers per day. Location fixed effects include shopping district dummies. Property characteristics include the construction year dummies, which are categorized as follows: <1650, 1650-1750, 1750-1850, 1850-1950, 1950-1980, 1980-2000, >2000 and 1005 (Basic Administration indication when construction year is unknow). *** p<.01, ** p<.05, * p<.1.*

Extension baseline model

The previous section discussed the results from the naïve model; the model without other independent variables and fixed effects, simply estimating the effect of footfall on retail vacancy. However, the estimated association between footfall and vacancy becomes slightly lower in column (2), when control variable *log storesize* is included in the model. No major changes arise when adding year fixed effects in column (3), where the association again only slightly decreases from 6.86% to 6.33%. Column (4) then investigates whether the association between footfall and vacancy is different after including location fixed effects. Here, the coefficients change more predominant. Where a 10% increase of footfall is now associated with a decrease of the odds of a retail property becoming vacant of 4.06%. Similar to Koster et al. (2019) and Oster (2019), the effects of adding control variables and fixed effects are also discussed by looking at a change in the Pseudo R-squared (hereafter R^2) in the regression models. Following the idea that an increase of the R^2 is very informative, with perfect predictability of the independent variables at $R^2 = 1$ (Oster, 2019). By looking at the model specifications (1 – 6) in table 3, the R^2 increases when the control variables and fixed effects are included separately. Even though the values for the R^2 remain relatively low for all models, compared to the R^2 in similar models from Koster et al. (2019) ranging from 0.0276 to 0.0442, the results in Figure 6 do not deviate much and are rather considered similar Nevertheless, it must be said that due to a scarcity of similar studies, and therefore similar models, it is difficult to compare the $R^2$and draw conclusions about its accuracy.

All in all, the model specification in columns (1 – 5) show us that footfall has a highly significant negative effect on the probability of a retail property becoming vacant. This is in line with our expectations based on previous research from Koster et al. (2019), which also found a negative association between footfall and retail vacancy. Therefore, we do not reject the first hypothesis: *H1: There is a negative association between footfall and retail vacancy,* and this supports the expectations that footfall is negatively associated with retail vacancy.

4.2 Sensitivity analysis

This section provides results to test our second hypothesis, whether the relationship between footfall and vacancy changes over time. Specifically, whether the regression models can compute significant results on the question whether the relationship between footfall and vacancy changed during Covid-19 (2020 and 2021). The last column (6) of table 3 includes an interaction variable that examines whether the relationship between footfall and vacancy depends on a particular year (over the time period 2015 – 2021). Even though the interactions appear to be significantly different from zero for all the years included in the analysis, the interactions are not significantly different from each other except for the difference between 2016 and 2017[6].Moreover, by looking at the pseudo R-squared, no further improvement of the model has been accomplished by adding the interaction terms. Therefore, we cannot conclude that the relationship between footfall and vacancy significantly depends on time. To make the results of Table 3 more transparent, appendix 4 is added with the full model results where all coefficients that are estimated are shown.

[6] To calculate whether the coefficients of the interaction variable footfall*year significantly differ from each other, I performed t-tests by using the estimated coefficients and the standard errors. The t-values were calculated as follows: 2017 vs. 2016 = (0.021-0.005)/(0.009-0.005) = 4; 2018 vs. 2017 = (0.024-0.005)/(0.021-0.005) = 1.1875; 2019 vs. 2018 = (0.036-0.005)/(0.024-0.005) = 1.6316; 2020 vs. 2019 = (0.061-0.005)/(0.036-0.005) = 1.8064; 2021 vs. 2020 = (0.074-0.005)/(0.061-0.005) = 1.2321. Only the coefficients of the interaction footfall*year between 2017 and 2016 significantly differ from each other as the calculated t-value of 4 exceeds the critical t-value of 1.96 at a 95% confidence level.

Table 4 presents repeats the logistic regression model from column (5) in table 3. This table shows the regression results per year in the analysis and is used to show whether there might be any significant differences between the years. Most importantly, is to look at possible differences over time concerning the years 2020 and 2021. Through the years 2015 to 2019 we can conclude that the relationship between footfall and vacancy appears to be slightly volatile. However, the coefficients for the years 2020 and 2021 appear to be visible lower compared to previous years. Which could indicate that the association between footfall and retail vacancy decreases in these years. For example, if footfall increases with 1% the odds ratio of a retail property becoming vacant decreases with 0.349% in 2020. The odds in 2021 are even lower, whereas the odds of a property becoming vacant decreases with 0.249% at a 1% increase of footfall. Overall, the chances that vacancy arises in the years 2015 – 2019 were lower, compared to 2020 – 2021, when there was a significant decrease in footfall.

Table 4 – Logistic regression output subdivided per year (2015 – 2021)

Footfall and Vacancy							
(Dependent variable: shop is vacant)							
	2015	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*
	Logit	Logit	Logit	Logit	Logit	Logit	Logit
Footfall *(log)*	-0.755***	-0.581***	0.418***	-0.532***	-0.479***	-0.349***	-0.249***
	(0.078)	(0.069)	(0.065)	(0.064)	(0.061)	(0.051)	(0.049)
Storesize *(log)*	-0.214***	-0.122***	-0.088***	-0.111***	-0.129***	-0.004	-0.071
	(0.041)	(0.037)	(0.034)	(0.035)	(0.0335)	(0.029)	(0.028)
No. of obs.	15,126	15,197	15,128	15,125	15,147	15,165	15,140
R^2	0.062	0.066	0.059	0.079	0.078	0.059	0.048
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Footfall is measured as the number of passing-by shoppers per day. Model specification (5) from table X is used to perform the logistic regression per year (No. of obs: number of observations)
**** p<.01, ** p<.05, * p<.1.*

Table 5 shows the regression results for two samples; 2015 – 2019 and 2020 – 2021. Similar to table 4, a weaker association between footfall and retail vacancy can be detected in 2020 – 2021, compared to 2015 – 2019. Therefore, table 5 shows that the chances on a decrease in retail vacancy in 2020 – 2021 is lower on average, compared to 2015 – 2019, when footfall increases.

Table 5 – Logistic regression output subdivided in two samples 2015-2019 and 2020-2021

Footfall and Vacancy		
(Dependent variable: shop is vacant)		
	2015 - 2019	*2020 - 2021*
	Logit	Logit
Footfall *(log)*	-0.548***	-0.282***
	(0.028)	(0.034)
Storesize *(log)*	-0.128***	-0.040***
	(0.016)	(0.019)
No. of obs.	75,890	30,305
R^2	0.063	0.051

*Notes: Footfall is measured as the number of passing-by shoppers per day. Model specification (5) from table X is used to perform the logistic regression per year (No. of obs: number of observations) *** p<.01, ** p<.05, * p<.1.*

It is important to consider why the association is weaker in 2020 and 2021. Following the four quadrant model (DiPasquale and Wheaton, 1992), and other studies (Talen & Park, 2021; Koster et al., 2019), one might expect that retail vacancy, and the association between footfall and retail vacancy, should be consistent unless there are (extreme) exogenous factors that would affect these market mechanisms, such as a financial crisis or an extreme demand shock. Nevertheless, the results in table 4 and 5, show that the association between footfall and retail vacancy is weaker in 2020 and 2021, implying that there are most likely other factors that influenced this association. One can think of, for example, the financial support measures of the Dutch government, which were intended to provide retailers with financial aid during Covid-19. These measures were intended to limit financial damage for retailers, but this also partly disrupted the functioning of the market as theorized by DiPasquale and Wheaton (1992). The fact that the government has provided massive financial support to retailers is an exceptional situation, and it has ensured that retailers were not hit too hard financially by the crisis caused by Covid-19. However, it has been argued that the financial support has also ensured that bankruptcies have been postponed, which would occur in normal crisis circumstances (ANP, 2021; RTL Nieuws, 2022). Nevertheless, it is still very hard to conclude with certainty what the direct reason is for the weakening association between footfall and retail vacancy.

5. CONCLUSION

Dutch shopping areas have faced many challenges in recent years, and the advent of covid-19 brought many uncertainties for retailers. The measures that were taken by the Dutch government to prevent the spread of the virus resulted in empty shopping streets and a significant decrease in footfall (Locatus, 2021). In assessing the performance of shopping areas, retail vacancy is often considered one of the key metrics (Rhodes, 2014; Liang, 2006; Talen & Park, 2021; Tsocalos, 1998). Nevertheless, only a few studies can be found that have looked at the potential of footfall in assessing the performance of shopping areas (Millington et al., 2015; Lugomer and Longley, 2018; Coca-Stefaniak, 2013). These studies have all shown that footfall can be an important metric in measuring the liveliness and attractiveness of shopping areas. Most importantly, only one study was found by Koster et al. (2019), which found a negative association between footfall and retail vacancy. Subsequently, this study revealed an expectation of a possible relationship between footfall and retail vacancy. Therefore, this research aims to examine the relationship between footfall and retail vacancy in Dutch shopping areas, and whether the results indicate any differences in this association over the years, especially during Covid-19 (2020 – 2021).

Following Koster et al. (2019), a Logistic Regression Model (LRM) was applied to test the theoretical hypotheses of this study. According to existing literature, control variables and fixed effects were added sequentially to the baseline model. In summary, the results indicate a negative association between footfall and retail vacancy, where with a 1% increase in footfall, the chances of a retail property becoming vacant decreases by 0.445%, ceteris paribus. Based on the results of the LRM, we cannot reject the first hypothesis and conclude that there is a negative association between footfall and retail vacancy. Second, after making samples in the data based on years, the sensitivity analyses show that the negative association between footfall and retail vacancy decreases in 2020 and 2021. Hence, the probability that vacancy will decrease in 2020 and 2021 is negligible, in contrast to the years before in the analysis. Finally, the results from the sensitivity analysis show that the association between footfall and vacancy changed over the years. Therefore our results support the second hypothesis. The results provide insights to answer the following central question posed in this thesis:

"What is the association between decreasing footfall rates and retail store vacancy in shopping areas of the Netherlands during Covid-19 lockdown periods?"

In conclusion, the results show that the chances that vacancy arises in the years 2015 – 2019 were lower, compared to 2020 – 2021, when footfall was significantly lower in Dutch shopping areas. Subsequently, the results from the LRM show a weakening association between footfall and retail vacancy during Covid-19, in the years 2020 and 2021. Which could mean that the consequences of

Covid-19, especially the effects of the measures taken by the Dutch government, had an impact on the retail sector.

As mentioned before, the literature regarding the association between footfall and retail vacancy is very scarce. Also, Koster et al. (2019) and Koster et al. (2021) explained the difficulty in using vacancy as a dependent variable. Hence, vacancy takes many forms (frictional, structural, financial), and this it is often complicated to observe. Although this may be a limitation of the study, the analysis was performed based on an extensive dataset. Data on different retail properties have been collected efficiently and consistently over the years and are therefore considered the best available. Overall, the contribution of this research mainly stems from the results of the baseline model and the sensitivity analyses. First, this research contributes to the emerging literature on the consequences of Covid-19 on the retail sector. Second, our unique findings show that the association between footfall and retail vacancy changes over the years, which has not been examined before. Third, the results confirm the explanatory power of footfall in association with retail vacancy, which in line with existing literature from Koster et al. (2019).

Limitations findings and methodology

Overall, some notions should be mentioned when discussing and interpreting the results. The results of this study both support and contradict our expectations based on existing literature. Although the results indicate a negative association between footfall and retail vacancy, the coefficients deviate from previous models by Koster et al. (2019), who estimated coefficients for footfall and retail vacancy ranging from 0.03% to 0.06%. Comparing the results highlights the following implications of this research. This study has possibly uncovered several essential (control)variables that correlate with retail vacancy. Koster et al. (2019) applied a pervasive analysis by including instrumental variables to deal with the problem of endogeneity. Not including instrumental variables in this study could lead to endogeneity issues and bias in the estimated coefficients Therefore, instrumental variables could have made the analysis more precise and valid. Second, the analysis performed in this research was a logistic regression on cross-sectional data. A limitation of analysing cross-sectional data in this context is that each observation is considered unique. Thus, retail properties are not observed over time. If retail properties would be observed over time, patterns could be examined, for example, when a property is vacant and when a property is occupied, in association with footfall.

Policy recommendations and future research

Overall, understanding the consequences of Covid-19 on the retail sector, and the economy in general, would be useful for policymakers. Policymakers have already indicated that, due to the lack of knowledge during the recent Covid-19 pandemic, they have found it difficult to estimate appropriate measures to be taken in such extreme situations (RIVM, 2022). As well as understanding the consequences of Covid-19, they have also indicated that knowledge about the pandemic is useful in preparing scenarios for a possible next pandemic. I believe that the results in this paper do not justify to call out direct actions. On the other hand, it can be concluded from the results that there might be a possible covid-effect on the relationship between footfall and retail vacancy. Nevertheless, based on the results and limitations of this study, a few recommendations for future research can be made, and some issues might deserve further empirical study.

First, this research was started shortly after the Dutch government withdrew the last Covid-19 measures. Therefore, the dataset does not contain data from the immediate period after removing the restrictions. Including footfall counts and data on vacancy after the withdrawal of the measures could provide insights into a possible recovery of footfall figures and whether this has any effect on retail vacancy. The latter could perhaps give a more accurate picture and could lead to more precise analysis of a possible impact of Covid-19 on the retail sector, which could help in formulating specific policy recommendations.

Second, with respect to the Pseudo R-squared values in the regression models, these appear to be considerably low. However, these values are similar to research from Koster et al. (2019) and there are not many other studies to compare these values with. A low R-squared value does not directly mean the analysis is inadequate, but more thorough literature research could maybe lead to a better comparison to possible similar models, and whether the R-squared values in this analysis could be considered adequate. A next promising line of research elaborates further on the main limitation of this research: possible omitted variables and possible endogeneity issues. Following Koster et al. (2019), and other studies regarding retail vacancy (Rhodes & Brian, 2014; Koster et al., 2019; Philp et al., 2021), more extensive models were implemented to deal with the latter issues. In all fairness, including more control variables and suitable instruments, similar to the models from Koster et al. (2019), could be a solution to strengthen the models of this study in general.

Third, the analysis performed in this research was a logistic regression on cross-sectional data. A more extensive analysis could be performed by analysing the development per retail property over time instead using a panel data structure. Analysing the retail properties over time could provide more insights into a possible pattern of when or whether a property becomes vacant.

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APPENDIX 1 – OVERVIEW COVID-19 RESTRICTIONS IN THE NETHERLANDS (2020/2021)

2020

January – In January 2020, the House of Representatives will be informed about an outbreak of a new corona virus in the Chinese city of Wuhan. The first corona infections are in Europe.

February – Many Dutch people who stayed in China or on cruise ships have returned to the Netherlands. The first corona infection in the Netherlands took place on February 27.

March – First lockdown - first restrictions against Covid-10 (Covid-19 became an official pandemic, E.U. Closing foreign borders, advice: work from home, closing of shops was not obligatory) Although, it was not obligatory for retailers to close, many of them did due to safety measures and fear for the virus (RIVM, 2022).

April – April 2020 is all about perseverance. The measures of March will be extended throughout April. At the end of April, the first relaxations such as the partial opening of primary schools will be announced. The cabinet is sending aid to the Caribbean part of the Kingdom. At the end of April, it will be announced that testing policy will be expanded for new target groups.

May – In May, the cabinet will present the second emergency package for jobs and the economy and will offer extra financial support for the Caribbean part of the Kingdom. After the May holidays, primary schools will partially reopen and nurseries will open completely. In mid-May, the cabinet will announce various relaxations as of June 1.

June – In June 2020, the cabinet will announce, among other things, a complete reopening of primary education. Face masks will be mandatory in public transport (public transport) and public transport will be fully operational again. Anyone with complaints can also be tested from 1 June. Also in this month a lot of attention for the corona dashboard, tourism and the summer holidays. Just like testing, tracing and vaccine development.

July – The month starts quietly. But in the course of the month, the number of infections increases again. Especially in the big cities. At the end of the month there will be a press conference about the concerns of the increasing infections in which everyone is called on to adhere to the basic rules. No additional measures have been taken for the time being.

August – In August, the infections continue to rise. That is why there are extra press conferences. It emphasizes the importance of the basic rules and announces new measures to get the virus under control. September – Dutch government is debating on implementing new Covid-19 restrictions

October – The tightened measures taken at the end of September appear to have insufficient effect. The cabinet will announce a partial lockdown in mid-October. Additional support measures will also be introduced.

November - The measures against the virus are not sufficient to reduce the infections enough. The partial lockdown was therefore extended at the end of October and will be intensified at the beginning of November. In mid-November, the cabinet will extend the intensified partial lockdown. In addition, the cabinet decides that wearing a mouth cap will be mandatory from 1 December and there will be a fireworks ban before the turn of the year.

December – At the beginning of December, the intensified partial lockdown will be extended again. In mid-December, Rutte announced a lockdown from the tower. A new mutation is emerging in England, the 'British variant' of the virus, which is more contagious than any mutation to date. At the end of December, the EMA will approve the first vaccine against COVID-19.

2021

January – The new year starts in the Netherlands in lockdown, but vaccinations also start in the first week of January. In the second week, the cabinet announces that the lockdown will be extended until the beginning of February and the curfew will be introduced at the end of January.

February – The lockdown will be extended at the beginning of February. But primary schools and childcare (with the exception of BSO) can open again as of 8 February. Socio-economic consequences are given a more prominent place in decision-making. Ordering and collection will be introduced from February 10. At the end of February, a cautious easing of the lockdown from the beginning of March will be announced.

March – The infections are increasing and the third wave is becoming visible. This month the lockdown will continue with only slight adjustments to the measures. We are eagerly looking forward to the start of summer with the prospect that the 3rd wave is over and everyone who wants it has been vaccinated. Then steps can be taken towards phasing out measures.

April - Infections continue to rise with a peak towards the end of April. No further relaxations will be announced mid-month, but the opening plan will be presented. At the end of the month, the number of infections decreases and the number of vaccinations increases. As a result, the first step of the opening plan can be taken at the end of April.

May - The earlier forecasts seem to be coming true, the infections are falling. Step 3 of the opening plan can be brought forward as a result. The vaccination program is getting even better and we can look forward to the reopening of society in the summer.

June - On June 5, the cabinet will end the lockdown. The number of infections and hospital admissions will drop significantly in June and the vaccination rate will increase to such an extent that step 4 in the opening plan can be put on June 26: society will in fact open again, taking into account the 1.5 meter measure.

July - It was no surprise that the virus would spread more after step 4 of the opening plan, but the increase in the number of infections is going very fast. Keeping 1.5 meters away in the catering industry is becoming the norm again and the closing time from 00.00 to 06.00 is reintroduced. Multi-day events are also not allowed to take place.

August - After the infections rose rapidly in July and measures were taken to contain the virus again, the infections have decreased. Due to this decrease, the cabinet sees no reason to increase the measures in force in August and will allow one-day festivals from mid-August under strict conditions. It is also announced that the 1.5 meter distance standard will be released from the new school year in MBO, HBO and at the universities.

September - After the recovery in July, the downward trend that started in August continues. The cabinet is therefore preparing to convert the 1.5-meter standard into advice as of 25 September. This means that a lot of related measures will also expire on that date.

October - In October it will become clear that vaccinations against the coronavirus are less effective in case of infection with the delta variant than with the alpha variant. The vaccinations for both variants have a high effectiveness against hospitalization.

November - The cabinet decides to use strict generic measures to limit contacts as much as possible. This will happen on November 2. A partial lockdown will be announced on November 12. On November 26, the first evening lockdown will be announced, with almost everything closing at 5 p.m.

December - On December 18, 2021, the week before Christmas, the cabinet will announce a hard lockdown that will take effect on December 19. This is done as a precaution. There is a peak in hospital occupancy due to the delta variant and the omikron variant is now gaining ground. Figures from Great Britain and South Africa show that this omikron variant is more contagious than previous variants. In addition, the cabinet is giving an extra boost to the booster campaign, with the aim that as many people as possible will have received their booster vaccination by January 2022.

APPENDIX 2 – LIST OF INCLUDED SHOPPING AREAS

Shopping areas (last count spring 2021)

Winkelgebied	Freq.	Percent	Cum.
Amsterdam Boven t Y	87	1.27	1.27
Buitenmere	53	0.77	2.05
Centrum Almelo	104	1.52	3.56
Centrum Amersfoort	305	4.46	8.02
Centrum Amsterdam	1009	14.74	22.76
Centrum Assen	239	3.49	26.25
Centrum Barneveld	85	1.24	27.49
Centrum Beverwijk	73	1.07	28.56
Centrum Bussum	104	1.52	30.08
Centrum Deventer	193	2.82	32.90
Centrum Goes	225	3.29	36.19
Centrum Gorinchem	84	1.23	37.41
Centrum Hardenberg	47	0.69	38.10
Centrum Harderwijk	99	1.45	39.55
Centrum Heerenveen	133	1.94	41.49
Centrum Heerlen	157	2.29	43.78
Centrum Helmond	179	2.62	46.40
Centrum Hoogeveen	142	2.07	48.47
Centrum IJsselstein UT	56	0.82	49.29
Centrum Leeuwarden	206	3.01	52.30
Centrum Leiden	362	5.29	57.59
Centrum Middelburg	175	2.56	60.15
Centrum Nieuwegein	108	1.58	61.72
Centrum Oosterhout NB	190	2.78	64.50
Centrum Roermond	239	3.49	67.99
Centrum Roosendaal	113	1.65	69.64
Centrum Rotterdam	435	6.36	76.00
Centrum Tiel	131	1.91	77.94
Centrum Tilburg	228	3.33	81.27
Centrum Utrecht	429	6.27	87.54
Centrum Veenendaal	232	3.39	90.93
Centrum Vlissingen	81	1.18	92.11
Centrum Waalwijk	109	1.59	93.70
Centrum Zaandam	169	2.47	96.17
Rotterdam Alexandrium	128	1.87	98.04
Rotterdam Zuidplein	134	1.96	100.00
Total	6843	100.00	

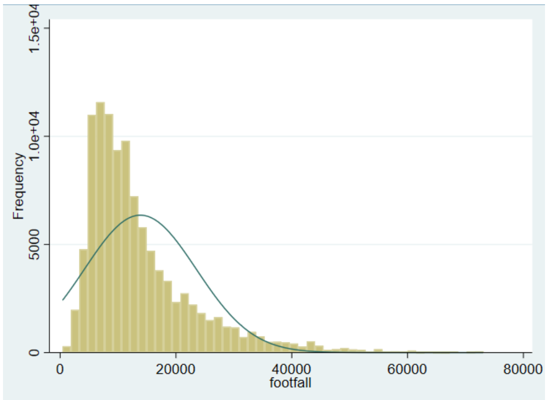
Shopping areas (last count fall 2021)

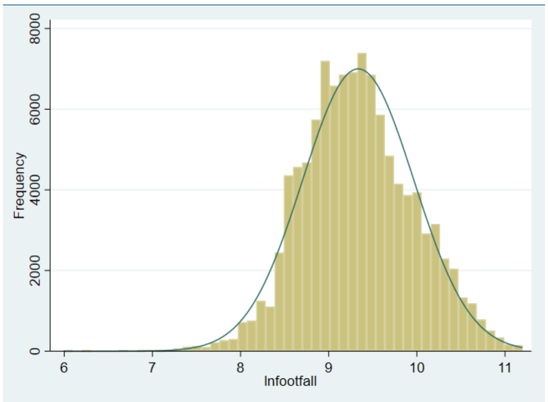
Winkelgebied	Freq.	Percent	Cum.
Centrum Alkmaar	366	4.34	4.34
Centrum Alphen aan den Rijn	136	1.61	5.95
Centrum Amstelveen	111	1.32	7.27
Centrum Apeldoorn	226	2.68	9.95
Centrum Arnhem	313	3.71	13.66
Centrum Bergen op Zoom	175	2.07	15.73
Centrum Coevorden	64	0.76	16.49
Centrum Delft	286	3.39	19.88
Centrum Den Helder	129	1.53	21.41
Centrum Doetinchem	137	1.62	23.03
Centrum Dordrecht	237	2.81	25.84
Centrum Ede GLD	167	1.98	27.82
Centrum Eindhoven	275	3.26	31.08
Centrum Enschede	315	3.73	34.82
Centrum Geleen	68	0.81	35.63
Centrum Haarlem	533	6.32	41.94
Centrum Heerhugowaard	93	1.10	43.05

Centrum Hellevoetsluis	84	1.00	44.04
Centrum Hengelo OV	116	1.38	45.42
Centrum Hoofddorp	110	1.30	46.72
Centrum Hoogvliet RT	62	0.74	47.46
Centrum Kampen	130	1.54	49.00
Centrum Lelystad	114	1.35	50.35
Centrum Lisse	83	0.98	51.33
Centrum Maarssen	51	0.60	51.94
Centrum Maastricht	610	7.23	59.17
Centrum Meppel	91	1.08	60.25
Centrum Oss	123	1.46	61.71
Centrum Ridderkerk	86	1.02	62.73
Centrum Rijssen	61	0.72	63.45
Centrum Rijswijk ZH	126	1.49	64.94
Centrum Schiedam	104	1.23	66.18
Centrum Sittard	203	2.41	68.58
Centrum Spijkenisse	126	1.49	70.08
Centrum Terneuzen	94	1.11	71.19
Centrum Uden	111	1.32	72.51
Centrum Valkenswaard	65	0.77	73.28
Centrum Venlo	312	3.70	76.98
Centrum Venray	90	1.07	78.04
Centrum Vlaardingen	84	1.00	79.04
Centrum Weert	158	1.87	80.91
Centrum Woerden	124	1.47	82.38
Centrum Zutphen	140	1.66	84.04
Centrum Zwolle	250	2.96	87.01
Centrum s Gravenhage	534	6.33	93.34
Centrum s Hertogenbosch	405	4.80	98.14
Haarlem Schalkwijk	79	0.94	99.08
Utrecht Overvecht	78	0.92	100.00
Total	8435	100.00	

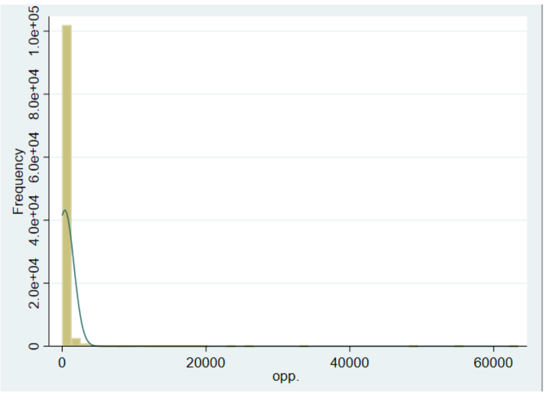
APPENDIX 3 – DATA TRANSFORMATION

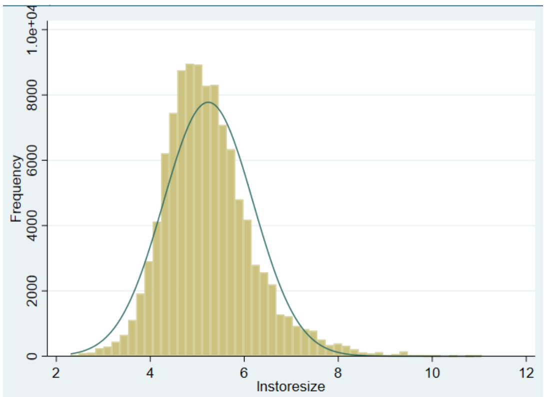
Footfall – lnfootfall





Store size – lnstoresize





APPENDIX 4 – REGRESSION OUTPUT PER MODEL

Logistic regression

vacancy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnfootfall	-.692	.018	-38.61	0	-.728	-.657	***
Constant	4.037	.164	24.63	0	3.716	4.358	***

Mean dependent var	0.087	SD dependent var	0.282
Pseudo r-squared	0.025	Number of obs	106195
Chi-square	1542.718	Prob > chi2	0.000
Akaike crit. (AIC)	61254.993	Bayesian crit. (BIC)	61274.139

**** p<.01, ** p<.05, * p<.1*

Logistic regression

vacancy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnfootfall	-.686	.018	-38.02	0	-.722	-.651	***
lnstoresize	-.04	.012	-3.36	.001	-.063	-.017	***
Constant	4.188	.17	24.60	0	3.855	4.522	***

Mean dependent var	0.087	SD dependent var	0.282
Pseudo r-squared	0.025	Number of obs	106195
Chi-square	1554.136	Prob > chi2	0.000
Akaike crit. (AIC)	61245.575	Bayesian crit. (BIC)	61274.294

**** p<.01, ** p<.05, * p<.1*

Logistic regression

vacancy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnfootfall	-.633	.018	-34.93	0	-.668	-.597	***
lnstoresize	-.045	.012	-3.79	0	-.069	-.022	***
2015b	0	.	.	.	.	.	
2016	.083	.047	1.78	.075	-.008	.174	*
2017	.181	.046	3.96	0	.091	.27	***
2018	.214	.045	4.71	0	.125	.303	***
2019	.313	.044	7.04	0	.226	.4	***
2020	.528	.043	12.32	0	.444	.612	***
2021	.59	.042	13.95	0	.507	.673	***
Constant	3.43	.176	19.49	0	3.085	3.775	***

Mean dependent var	0.087	SD dependent var	0.282
Pseudo r-squared	0.030	Number of obs	106195
Chi-square	1903.229	Prob > chi2	0.000
Akaike crit. (AIC)	60908.481	Bayesian crit. (BIC)	60994.639

**** p<.01, ** p<.05, * p<.1*

Logistic regression

vacancy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnfootfall	-.634	.018	-34.90	0	-.67	-.598	***
lnstoresize	-.046	.012	-3.87	0	-.07	-.023	***
2015b	0	.	.	.	.	.	
2016	.083	.047	1.79	.074	-.008	.175	*
2017	.182	.046	3.98	0	.092	.271	***
2018	.215	.045	4.74	0	.126	.304	***
2019	.314	.044	7.07	0	.227	.402	***
2020	.529	.043	12.34	0	.445	.613	***
2021	.591	.042	13.96	0	.508	.674	***
sh_dist	.002	0	4.90	0	.001	.003	***

Constant	3.354	.177	18.96	0	3.007	3.7	***

Mean dependent var	0.087	SD dependent var	0.282
Pseudo r-squared	0.031	Number of obs	106195
Chi-square	1927.236	Prob > chi2	0.000
Akaike crit. (AIC)	60886.474	Bayesian crit. (BIC)	60982.205

*** *p<.01, ** p<.05, * p<.1*

Logistic regression

vacancy	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnfootfall	-.555	.019	-29.29	0	-.592	-.518	***
lnstoresize	-.076	.012	-6.35	0	-.1	-.053	***
2015b	0	.	.	.	.	.	
2016	.087	.047	1.87	.061	-.004	.179	*
2017	.188	.046	4.10	0	.098	.277	***
2018	.22	.045	4.85	0	.131	.309	***
2019	.32	.045	7.19	0	.233	.408	***
2020	.538	.043	12.53	0	.454	.622	***
2021	.612	.042	14.43	0	.529	.695	***
sh_dist	.001	0	2.18	.029	0	.002	**
cs1_dum	-.997	.103	-9.71	0	-1.199	-.796	***
cs2_dum	-.344	.07	-4.89	0	-.482	-.207	***
cs3_dum	-.438	.062	-7.09	0	-.56	-.317	***
cs4_dum	-.486	.052	-9.41	0	-.587	-.385	***
cs5_dum	-.296	.042	-7.00	0	-.378	-.213	***
cs6_dum	-.072	.043	-1.68	.094	-.155	.012	*
cs7_dum	-.07	.044	-1.58	.114	-.157	.017	
o	0	.	.	.	.	.	
cs9_dum	-.339	.145	-2.34	.019	-.623	-.055	**
Constant	3.071	.188	16.33	0	2.703	3.439	***

Mean dependent var	0.087	SD dependent var	0.282
Pseudo r-squared	0.037	Number of obs	106195
Chi-square	2347.618	Prob > chi2	0.000
Akaike crit. (AIC)	60482.092	Bayesian crit. (BIC)	60654.407

*** *p<.01, ** p<.05, * p<.1*

APPENDIX 5 – CORRELATION MATRIX

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) vacancy	1.000																
(2) ln_footfall	-0.119	1.000															
(3) storesize	-0.025	0.140	1.000														
(4) sh_dist	0.015	-0.028	0.025	1.000													
(5) shopping_area_~e	0.074	-0.327	0.009	0.084	1.000												
(6) pr_fr	-0.000	-0.044	0.020	-0.022	-0.076	1.000											
(7) pr_dr	0.022	-0.036	0.041	-0.050	0.214	-0.049	1.000										
(8) pr_ol	0.006	0.017	0.007	0.034	0.156	-0.038	0.776	1.000									
(9) pr_gel	-0.002	-0.052	0.004	-0.174	0.054	-0.046	-0.099	-0.077	1.000								
(10) pr_fl	0.017	-0.048	-0.020	-0.045	0.127	-0.016	-0.034	-0.026	-0.032	1.000							
(11) pr_nh	-0.053	0.119	-0.066	-0.407	-0.255	-0.072	-0.155	-0.120	-0.146	-0.050	1.000						
(12) pr_zh	-0.009	0.028	0.009	0.196	-0.131	-0.075	-0.160	-0.124	-0.151	-0.052	-0.236	1.000					
(13) pr_ut	-0.012	0.044	0.003	0.160	0.122	-0.049	-0.105	-0.082	-0.100	-0.034	-0.156	-0.161	1.000				
(14) pr_nb	0.024	-0.021	0.024	0.176	-0.005	-0.058	-0.125	-0.097	-0.118	-0.041	-0.185	-0.191	-0.126	1.000			
(15) pr_zee	-0.000	-0.034	0.006	-0.001	0.114	-0.028	-0.059	-0.046	-0.056	-0.019	-0.088	-0.090	-0.060	-0.071	1.000		
(16) pr_lim	0.030	-0.033	-0.010	0.202	0.013	-0.058	-0.123	-0.096	-0.116	-0.040	-0.182	-0.188	-0.124	-0.147	-0.070	1.000	
(17) cons_year_N	0.069	-0.299	0.076	0.223	0.373	0.023	0.093	0.061	0.063	0.059	-0.384	0.105	0.028	0.065	0.037	0.043	1.000