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Agglomeration, Diversification and Redevelopment of Retail

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Agglomeration, Diversification and Redevelopment of Retail

Song Zhang

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University of Groningen.

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university of
 groningen

Agglomeration, Diversification and Redevelopment of Retail

PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. C. Wijmenga
and in accordance with
the decision by the College of Deans.

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Beijing

May, 2021

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1.1 Motivation

The retail sector, covering all economic activities related to providing goods and services to individual or household consumers, is of great importance worldwide. For example, the retail sector accounts for about 5% of GDP across OECD economies. Its economic impact and a number of other factors make the retail sector an indispensable and paramount part of modern society and the economy.

It is important here to stress that this thesis addresses real estate issues related to retail. As such, the focus is mainly on bricks-and-mortar retail and online shopping is not considered. As such, when referring to the retail sector in this thesis, we are including only the more traditional physical outlets.

First, in highlighting the major role of the sector, one can observe that the retail sector is very labor-intensive and provides a large number of job opportunities. According to the OECD, on average, 1 in 12 workers (about 8%) are employed in the retail sector across OECD economies. To illustrate this, Figure 1.1 presents the number of jobs provided by the Dutch retail sector and the percentage of retail jobs in all jobs from 1996 to 2011.¹ The total number of jobs in the Dutch retail sector increased from about 870,000 in 1996 to about 1,095,000 in 2011. During this period, retail jobs accounted for on average about 13.5% of all jobs in the Netherlands, significantly above the OECD average. This high figure may in part be due to the significant number of part-time jobs in this sector. Indeed, Figure 1.1 shows that, in the Netherlands, a large and growing proportion of all retail jobs were part-time between 1996 to 2011.

Second, the retail sector occupies a key position in value chains. Consumers purchase goods and services and gain access to leisure and entertainment activities through the retail sector (Kooijman, 2002). Upstream sectors or businesses sell their products to consumers, and collect feedback on their products, through the retail sector (Kaplinsky & Morris, 2001). That is, the retail sector services the final demand and functions as the interchange that connects producers and consumers.

Third, the retail sector shapes modern urban areas. The morphology and spatial structure of many inner cities, where shops, supermarkets, restaurants, cafes, and

¹Source: LISA.

Figure 1.1: Number of jobs in the Dutch retail sector and the percentage of retail jobs in all jobs from 1996 to 2011

other retail amenities are concentrated, are heavily determined by the distribution of the retail sector (Anas et al., 1998; Burger et al., 2014; Teulings et al., 2018). Indeed, the popularity of a city is strongly related to the attractiveness of its retail amenities (Öner, 2017). Access to retail amenities has an important impact on people's quality of life, and this drives people to move into or visit a city (Brueckner et al., 1999; Chen & Rosenthal, 2008). Brueckner et al. (1999) commented that "when the center has a strong amenity advantage over the suburbs, the rich are likely to live at central locations." Chen & Rosenthal (2008) nuance this by indicating that while young highly educated people move towards places with high quality business environments, older people move toward places with highly valued consumer amenities.

Fourth, retail properties are popular investment targets for investors. Real estate investments have proven to be attractive to investors because of the relatively stable cashflows and competitive returns (Gujral et al., 2020). Compared to other commercial properties, the rental incomes from retail properties are less volatile over economic cycles (Ibanez & Pennington-Cross, 2013). As such, including retail properties in their portfolio may well be seen as a good investment strategy by investors and their advisors. Figure 1.2 shows the average retail rents in the Netherlands from 1996 to 2011.² Between 1997 to 2011, the average nominal retail rents fluctuated be-

²Source: Strabo.

Figure 1.2: Average nominal and real retail rents in the Netherlands from 1996 to 2011

tween 230 and 270 euros per m^2 , although in real terms average retail rents show a downward trend.

Despite its historic importance, the retail sector is currently facing a lot of threats mainly driven by the rapid development of online shopping and the associated shifts in consumer behavior. Figure 1.3 shows the year-on-year changes in retail turnover through different channels in the Netherlands from 2005 to 2019.³ It is apparent that the turnover in online shopping has been growing at a much faster rate than the overall sector.⁴ As can be seen in the figure, year-on-year changes in turnover across the entire retail sector have been below 5%. However, online shopping has greatly outperformed the sector as a whole in almost every year shown. Most notably, online annual turnover growth in online shopping exceeded 15% in 2015, 2016, and 2017. While it remains unclear to what extent online shopping affects consumers' behavior in visiting physical retail outlets, it is reasonable to assume that online shopping has replaced some of the traditional in-store shopping (Weltevreden, 2007; Weltevreden & Van Rietbergen, 2007).

One of the first signals of how online shopping is affecting consumer behavior by replacing traditional in-store shopping is perhaps the increasing number of empty

³Source: Statistics Netherlands.

⁴In Figure 1.3, all retail includes both online shopping and bricks-and-mortar retail. If the turnover changes in online shopping outperform that of all retail, it is apparent that online shopping must also outperform bricks-and-mortar retail - i.e. what is referred to as the retail sector in this thesis.

Figure 1.3: Year-on-year changes in retail turnover in the Netherlands from 2005 to 2019

retail properties. Figure 1.4 shows the retail vacancy rate based on floor space in the Netherlands from 2003 to 2018.⁵ Before 2010, the retail vacancy rate was fairly stable and remained below 6%. However, since 2011, the retail vacancy rate has increased quite rapidly and peaked in 2016 with a vacancy rate of more than 10%. Although online shopping may not be the only reason for these increases, there is evidence of a link (Baen, 2000; Tonn & Hemrick, 2004; Weltevreden, 2007). Indeed, the Netherlands is not the only country to experience a high retail vacancy rate. According to Locatus, many European cities, including Brussels, Marseilles and Lisbon, have faced retail vacancy rates of more than 10% in recent years.

While the retail sector already seemed increasingly under threat, the outbreak of COVID-19 may well accelerate the changes taking place. The measures taken by governments to tackle the pandemic have greatly affected the supply, demand, and daily operations of the retail sector. Many retail activities have been shut down during lockdowns. Even when lockdowns are lifted, social distancing rules may limit retailers' capacity to serve consumers. Meanwhile, influenced by the pandemic, consumers are being more cautious in spending on non-essential goods and services, and spend more on essential goods such as food, medicine, and household sup-

⁵Source: Locatus and PBL.

Figure 1.4: Retail vacancy rate (by floor area) in the Netherlands from 2003 to 2018

plies (Gujral et al., 2020; OECD, 2020).⁶ For example, in the United States, while the turnover of clothing shops dropped year-on-year by 89.3% in April 2020, the turnover of grocery stores increased by 13.2% according to the Census Bureau of the United States. In the EU, while the turnover in non-food products year-on-year dropped by 23.8% in April 2020, the sales of food, beverages, and tobacco increased by 1.2% according to Eurostat. Consumers' shopping behavior has also changed because of the pandemic with increasing numbers of consumers reducing their visits to physical retail properties and turning to online shopping. For example, according to Nielsen Scantrack, in France the market share of online shopping had increased to more than 10% of total consumer goods sales at the start of April 2020, compared to less than 6% in 2019. According to the UK's Office for National Statistics, the proportion of retail expenditure online increased from 19.1% in April 2019 to 30.7% in April 2020. In the Netherlands, the percentage of consumers who prefer to shop online has increased to 35% during the pandemic compared to 16% before the pandemic according to NRW (Dutch Council of Shopping Centers).

The apparent meltdown of the retail sector may have disastrous consequences for society and the economy. First, the retail sector is very labor intensive, so any disruptions in the retail sector may lead to disproportionate employment problems. Given

⁶Even if, compared to non-essential retail businesses, essential ones are less affected by the pandemic, they still operate in very difficult conditions with disruptions in supply chains, labor shortages, and occasionally high demand for specific items (OECD, 2020).

that, as was shown in Figure 1.1, the retail sector employs a lot of part-time and casual workers who are not well covered by traditional social welfare systems, the social consequences of unemployment in this sector may be particularly severe. Second, the increasing retail vacancy rates may impose negative externalities on neighborhoods (Teulings et al., 2018; Koster et al., 2019), which may lead to a fall in the attractiveness of neighborhoods and cities. Third, if consumers continue to visit less frequently and spend less at physical retailers, the operating income of both retailers and, as a knock-on effect, retail property investors may decrease. The value of retail properties may then in turn also fall. This may increase the perceived risk of investing in retail real estate and discourage the construction of new retail properties.

1.2 Research questions

The retail sector is today facing many challenges and more can be expected in the future. To be better prepared for the future, a deep and thorough understanding of the retail sector is needed. Improving the understanding of the retail sector is of great interest to retailers, investors, and policymakers. The aim of this thesis is to gain deeper insights into the retail sector, with a particular focus on the nature of retail real estate in urban areas where retail amenities are concentrated. As such, the main research question of this thesis is formulated as:

“What are the consequences of the changing retail landscape in urban areas?”

In the following subsections, we present discussions and derive research sub-questions related to four aspects:

- (a) Location patterns of retail properties;
- (b) Tenant mix within shopping districts;
- (c) Real estate depreciation;
- (d) Retail revitalization and inner city deprivation.

1.2.1 Location patterns of retail properties

The first objective is to investigate the location patterns of retail properties. The clustering of economic activities has long fascinated both economists and geographers since the publication of (Marshall, 1890). In recent decades, theories and empirical approaches addressing the topic of clustering have developed rapidly (see, e.g., Ellison & Glaeser, 1997; Duranton & Puga, 2004; Rosenthal & Strange, 2004; Duranton & Overman, 2005; Puga, 2010; Billings & Johnson, 2012; Lang et al., 2020). However, most published research focuses on the industrial sector (see, e.g., Maurel & Sédillot, 1999; Rosenthal & Strange, 2004; Duranton & Overman, 2008; Goldman et al., 2019). Clustering of the retail sector has been relatively under-researched. However, clearly, just as in other sectors of the economy, the retail sector has a strong tendency to cluster. The very existence of shopping districts and shopping centers shows the importance of clustering for the retail sector. To gain further insight into location patterns in the retail sector, we first need to investigate how the retail properties in different retail segments cluster. It is quite possible that retail properties in different retail segments may have distinct preferences over clustering. It is therefore important to examine the location patterns of retail properties in different retail segments.

The research questions related to this sub-objective are:

What are the location patterns of retail properties? What are the differences in location patterns of retail properties in different retail segments?

1.2.2 Tenant mix within shopping districts

The next objective is to gain greater insight into the agglomeration of retail properties. Shopping districts are formed by retail properties becoming concentrated in a certain area. Shopping districts can provide various goods and services to consumers. The diversity of retail tenants in a shopping district is labeled the tenant mix. Earlier research has shown that the agglomeration and diversity of retail properties therein has benefits for both consumers and retailers (Mulligan, 1984; Brueckner, 1993). For consumers, the agglomeration of retail properties can reduce their

travel and time costs (Eaton & Lipsey, 1982; Claycombe, 1991; Stahl, 1982; Glaeser et al., 2001; Teller & Reutterer, 2008). For retailers, agglomeration can help to improve their turnover and productivity through the presence of externalities (Brueckner, 1993; Wheaton, 2000; Koster et al., 2014, 2019). However, most previous publications on tenant mix have only considered shopping malls. The literature on tenant mix in shopping districts is very limited. One reason for this is that it is difficult to clearly define shopping districts. Therefore, it is first necessary to come up with an approach to delineate shopping districts, and then to investigate how tenant mix affects shopping districts.

The research questions related to this sub-objective are:

What are the boundaries, shapes and sizes of high street shopping districts? How is tenant mix related to the attractiveness of shopping districts?

1.2.3 Real estate depreciation

As with all tangible assets, real estate properties lose value with age. The depreciation of real estate properties is a crucial aspect of understanding the dynamics of real estate properties. Grasping the complexities of real estate depreciation has important implications for both investors and policymakers. In recent decades, a rich literature on residential property depreciation has developed (see, e.g., Smith, 2004; Francke & Van de Minne, 2017). However, only a few studies have attempted to estimate the depreciation of commercial properties. One of the notable exceptions is by Bokhari & Geltner (2018) which estimate the depreciation of commercial real estate properties in the US and concluded that the depreciation rates of commercial real estate properties differ between metropolitan areas and across market segments (office, retail, and industrial). A logical follow-up question is what drives this variation in depreciation rates across regions and market segments. An obvious possibility is regional economic conditions since fluctuations in real estate prices have been linked to local economic conditions (Plazzi et al., 2010; Rosenthal, 2014). As such, depreciation rates can be expected to be also related to regional economic drivers. The dearth of literature that examines depreciation rates in conjunction with regional economic

drivers prompts questions on this issue.

The consequent research questions related to this sub-objective are:

To what extent do commercial real estate properties depreciate? By how much do the depreciation rates vary across regions and market segments? What regional economic drivers drive this variation?

1.2.4 Retail revitalization and inner city deprivation

Assuming real estate properties continually depreciate, there will come a time when the structural value of real estate properties will reach zero. The likely ending for real estate properties with almost no structural value will be demolition or redevelopment. Given the presence of externalities, the redevelopment of a single real estate property may also influence surrounding neighborhoods. As a result, it is often assumed by policymakers that redevelopment can be used as a tool to fight neighborhood deprivation (Ahlfeldt et al., 2017). Indeed, previous research has found empirical evidence of externalities from redevelopment projects, including ones tackling brownfield sites (Kiel & Zabel, 2001), cultural heritage (Been et al., 2016), industrial heritage Van Duijn et al. (2016), local parks (Livy & Klaiber, 2016) and public housing (Schwartz et al., 2006). However, research on the externalities of redeveloping retail properties is very limited. Here, our aim is to contribute to the literature by examining the external effects of retail property redevelopment on nearby neighborhoods.

The research questions related to this sub-objective are:

What are the external effects of redeveloping retail properties on the surrounding neighborhoods? How do these external effects vary over time and across space?

1.3 Thesis outline

In Chapter 2, we explore the location patterns of retail properties by using granular data on retail properties in the Netherlands. We use the distance-based approach proposed by Duranton & Overman (2005) to measure the location patterns of retail

properties in the Netherlands. The basic idea behind this approach is to calculate the distances between every pair of retail properties in the same retail segment and estimate the density of these bilateral distances. In this paper-based chapter, we answer the first research question through discussions on three major issues. First, we compare the location patterns of retail properties in different retail segments because retail properties in different segments may have different clustering preferences. Second, we investigate the location patterns of newly-opened retail properties relative to existing retail properties to see if these location patterns are dynamic. Third, we consider the distribution of employees in the Dutch retail sector and compare the location patterns of male employees to those of female employees.

In Chapter 3, we focus on the relationship between tenant mix and the attractiveness of shopping districts. As identified in the second research question, we need to delineate the boundaries, shapes and sizes of shopping districts. To do this, we again utilize the granular data on retail properties in the Netherlands. Here, we propose an innovative methodology to delineate shopping districts. First, we divide the whole Netherlands into small grids and calculate the kernel density of retail properties for each grid. Second, we merge adjacent grids to form a shopping district if the kernel density of each grid exceeds a certain threshold. Once shopping districts are delineated, we then calculate the tenant mix of each shopping district based on the Herfindahl Index. Since it has been argued that the attractiveness of shopping districts should be capitalized in the retail rents (Pashigian & Gould, 1998; Cho & Shilling, 2007; Ahlfeldt et al., 2015), in the second part of this chapter we investigate the relationship between tenant mix and retail rents in shopping districts. First, we use both linear and semiparametric functions to examine the relationship between tenant mix and retail rents. Second, we use a difference-in-difference model to test for unobserved heterogeneity in retail rents. Indeed, we show that the heterogeneity in retail rents is largely explained by the variation in the tenant mix of shopping districts.

In Chapter 4, we analyze the depreciation of real estate using commercial real estate sales data from 16 European countries. In this chapter, we first deduce depreciation rates for commercial real estate properties across Europe. To this end, we develop a hedonic pricing model with age and age-squared terms to capture

the depreciation rates. In particular, we interact country dummies with age and age-squared terms to capture the variation in depreciation rates across countries. Second, we explore further the regional variations in depreciation rates across Europe by connecting depreciation rates to economic drivers. To achieve this, we use NUTS 3 level aggregated economic drivers that reflect disposable income, real GDP, and unemployment rate, and interact these regional economic drivers with the age terms. Through this, we can begin to understand the interplay between depreciation rates and regional economic drivers.

In Chapter 5, we study the external effects of real estate redevelopment by focusing on the redevelopment of shopping centers in the Netherlands. We examine almost 300 shopping centers that were redeveloped in the Netherlands between 1992 and 2010 and combine them with residential property transaction data to investigate the external effects of shopping center redevelopment on surrounding residential property prices. We apply a difference-in-difference framework to control for unobserved heterogeneity. Specifically, following the approach used in Schwartz et al. (2006), Van Duijn et al. (2016) and Been et al. (2016), we incorporate spatial and temporal interaction variables to capture the dynamics of external effects given that the external effects associated with shopping centers are dynamic in nature.

Chapter 6 brings this thesis to a conclusion. We first summarize previous chapters with discussions on the findings and the conclusions that can be drawn. We then discuss the policy implications that can be derived from our research. Finally, we offer suggestions for possible future research.

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Chapter 2

Location Patterns of Retail Real Estate Properties in the Netherlands

Abstract

Retail properties have a tendency to cluster. However, retail properties in different retail segments may have different preferences over clustering. In this paper, I explore the location patterns of various types of retail properties using granular data on retail properties in 14 retail segments in the Netherlands and applying a distance-based kernel density methodology. I find that retail segments that provide specialized and heterogeneous goods and services tend to be more densely clustered together. Further, newly-opened retail properties in most retail segments are more dispersed than existing properties. Finally, males employed in the retail sector have a more clustered distribution pattern than female employees.

Keywords: *clustering, retail, location pattern, kernel density confidence intervals*

2.1 Introduction

Retail properties have a tendency to be clustered. Shopping districts and shopping centers are two manifestations of the clustering phenomenon. The clustering of the retail sector is perceived as beneficial for both consumers and retailers (Mulligan, 1984; Brueckner, 1993). When on a shopping trip, consumers tend to compare the products and prices of products in a variety of similar stores. The clustering of these stores can save consumers' travel and time costs (Eaton & Lipsey, 1982; Stahl, 1982; Claycombe, 1991; Teller & Reutterer, 2008). For retailers, the clustering of retail properties can attract more consumers and thus improve the productivity of retailers through the existence of externalities (Wheaton, 2000; Foster et al., 2006; Koster et al., 2019; Zhang et al., 2020b).

Economists have been fascinated by this tendency for economic activities to cluster in certain areas since this was highlighted by Marshall (1890). Understanding the effects of clustering has had a profound impact in both academic and practical fields. In recent decades, empirical approaches to measure this phenomenon have made perceptible progress (Ellison & Glaeser, 1997; Maurel & Sédillot, 1999; Devereux et al., 2004; Duranton & Overman, 2005; Marcon & Puech, 2010; Billings & Johnson, 2012; Lang et al., 2020). However, most of the papers that apply these new empirical approaches have focused on the industry sector of the economy (Duranton & Overman, 2008; Klier & McMillen, 2008; Goldman et al., 2019). The clustering of the retail sector has been relatively ignored. However, Burger et al. (2014) have analyzed the dependence of retail sector on regional spatial structure and conclude that the retail sector is less clustered in more polycentric and more dispersed regions. Zhou & Clapp (2015) examine the location decisions of retail stores by focusing on the openings of anchor stores in the United States and conclude that new stores are more dispersed than existing stores.

The aim of this paper is to provide more detailed insights into the location distribution of the retail sector by focusing on identifying the various clustering patterns across retail segments. To this end, I draw on granular data on retail properties that are registered at the Dutch Chambers of Commerce. For each retail property, detailed

information including its address, SBI sector classification⁷, and number of employees can be retrieved. I use a distance-based methodology created and then further developed by Duranton & Overman (2005, 2008) to measure location patterns in the retail sector in the Netherlands. The basic idea underpinning this methodology is to calculate the distances between every two retail properties in the same retail segment and estimate the density distribution of these bilateral distances. This method is not sensitive to spatial scale and allows comparison across retail segments.

Three major issues are discussed in this paper. First, I compare the location patterns of various retail segments in the Netherlands. Despite all the recognized benefits of clustering, clustering also brings competition between retailers. Retailers in some retail segments will be more sensitive to competition and thus benefit less from clustering. It can be expected that different retail segments will have different clustering patterns. For example, clothing and furniture stores are inclined to cluster in a certain area because they offer heterogeneous goods with diverse designs, qualities, and prices. Conversely, stores selling convenience goods such as supermarkets provide more similar products and so that the desire to avoid competition will induce them to seek more dispersed locations. It is therefore important to explore the different preferences and location patterns of each segment within the retail sector. In line with expectations, my analysis shows that retail segments that provide specialized and heterogeneous goods and services are more concentrated in terms of location, while those segments that provide homogeneous goods and services are more dispersed.

Second, I investigate and compare the location patterns of newly-opened stores and existing stores. The location choices of newly-opened stores are influenced by the locations of existing stores. Previous research shows that the location patterns of establishments change dynamically over time (Dumais et al., 2002; Duranton & Overman, 2008; Zhou & Clapp, 2015), that is that location choices are not persistent. For future planning, it is important to understand if the location patterns of the Dutch retail sector are also dynamic and if there are any differences across retail segments. Here, my analysis shows that, for most retail segments, newly-opened stores

⁷SBI sector classification is a hierarchical classification of economics activities that CBS (*Statistics Netherlands*) uses to classify business units according to their main activity.

are more dispersed than existing stores.

Finally, the third issue that I consider in this paper is if there are gendered differences in employment distribution in retail segments in the Netherlands. Previous research has primarily utilized establishment-level data, and therefore provides no information on employment distribution in the industry or retail sector. In exploring this issue, it has been possible to gain insights into the distribution of employment across the Dutch retail sector. I find that, in the majority of retail segments, male employees are more clustered over shorter distances than female employees.

This paper contributes to the literature in several ways. First, it contributes to the literature on Dutch retail properties. To the best of my knowledge, this is the first paper that uses the Duranton & Overman (2005) distance-based methodology to investigate the location patterns of retail properties in the Netherlands. Second, this paper contributes to the literature on the agglomeration economy. I compare the location patterns of various retail segments in the Netherlands and explore the dynamics in their location patterns. I show that retail properties in different segments may have different preferences over clustering and location patterns. Third, this paper expands the discussion on the distribution of retail properties to the distribution of retail employees. Using the registered number of employees and detailed individual information, I am able to demonstrate gendered differences in employee distribution.

The remainder of this paper is organized as follows. Section 2.2 discusses the theoretical background on why different retail segments may have different location patterns. Following this, Section 2.3 describes the data and summary statistics. Section 2.4 introduces the Duranton & Overman (2005) distance-based methodology for agglomeration analysis. Section 2.5 presents the results of the analysis and Section 2.6 draws conclusions.

2.2 Clustering of retail real estate properties

The reasons why industries tend to cluster have been thoroughly discussed in previous publications. However, it is also known that the clustering in the retail sector shows some different characteristics to those in manufacturing industries (Ellison et

al., 2010; Puga, 2010). From the perspective of the retail sector specifically, there are several reasons for the clustering of retail properties. First, concentrating retail properties in a small area can help broaden the catchment area and increase the number of visiting customers (Zhang et al., 2020a,b). Second, the clustering of retail properties can lower the operation costs of retailers, including advertising costs and the transportation costs associated with acquiring and distributing their merchandise. Third, the clustering of the retail sector means that a retailer can enjoy the externalities brought about by other retailers (Ellison et al., 2010; Koster et al., 2019).

However, the clustering of retail properties from the same segment may also have some negative effects. One of the biggest disadvantages is the competition from other retailers. For many retailers, their products are substitutes for each other's and so concentration may increase the competition among themselves. As a result, these retailers may choose to locate remotely from each other to avoid competition.

The existence of advantages and disadvantages of clustering leads to the fact that retailers from different retail segments may have distinct preferences over location patterns (Zhou & Clapp, 2015). For example, supermarkets sell products that are fairly homogeneous and substitutable so they may opt for more dispersed locations. Conversely, clothes and furniture stores are better able to provide heterogeneous products that cannot be fully substituted, which makes concentration more attractive. Indeed, in many Dutch cities, and elsewhere, one observes concentrations of clothes stores and of furniture stores in the same street or in a certain area. The aim of the empirical part of this paper is to investigate which retail segments have the greatest tendency to concentrate competing outlets.

2.3 Data

In exploring the location patterns of retail properties in the Netherlands, I have been able to draw on the LISA dataset. This dataset is collected and updated on a yearly basis and includes all retail properties that are registered at the Dutch Chambers of Commerce on January 1st of each year. For each retail property, it contains detailed information including the property's address, the name of the retail tenant, SBI-sector classification, and the number of employees in the corresponding year.

Figure 2.1: Retail properties registered at the Dutch Chamber of Commerce in 2011

Note: This figure shows the retail properties registered at the Dutch Chamber of Commerce. Every blue dot in the figure represents one retail property.

Notably, it also contains information about the number of male and female employees at each property. Each SBI classification code refers to a single category of economic activity. The SBI classification coding system contains 2 to 5 digits. The fewer digits used, the broader the classification. In this study, I use the 3-digit SBI classification code⁸ which categorizes all the retail properties into one of 14 retail seg-

⁸The 4-digit and 5-digit SBI classification codes are considered too detailed in that many retail segments classified using 4-digit or 5-digit SBI classification codes are not that different and therefore not expected to show different location patterns. On the other hand, the 2-digit SBI classification code is too broad. In this situation, the 3-digit SBI classification code is a logical choice given the aims of this paper.

Table 2.1: Summary statistics of retail segments

	Number	Percentage
Retail sale in non-specialised stores	5,952	2.96%
Specialised shops selling food and beverages	12,357	6.15%
Petrol stations	2,029	1.01%
Shops selling consumer electronics	3,893	1.94%
Shops selling other household equipment	14,839	7.39%
Shops selling reading, sports, camping and recreation goods	8,596	4.28%
Shops selling other goods	44,166	21.99%
Market sale	9,648	4.8%
Retail sale not via stores and markets	21,171	10.54%
Restaurants	22,580	11.24%
Bars	10,473	5.22%
Travel agencies and tour operators	3,797	1.89%
Tourist information and reservation services	944	0.47%
Hairdressing and beauty treatment	40,375	20.11%
Total	200,820	100%

Note: This table presents the summary statistics of retail segments including the number of retail properties and the percentage of each segment.

ments.⁹ Using the full postal address, I can match the granular retail property data with the all-parcel file¹⁰ to obtain the geo-location information of every retail property, thereby making it possible to calculate the distances between every two retail properties in each retail segment.

In order to compare the location patterns of retail properties in the various retail segments, I selected the LISA dataset for 2011 for further analysis. Figure 2.1 depicts the distribution of all the retail properties registered at the Dutch Chamber of Commerce in 2011. Every blue dot represents one retail property. It can be seen that the retail properties in the LISA dataset are distributed throughout the whole Netherlands.

Table 2.1 presents the summary statistics of retail properties in each retail segment, including the numbers and percentages of retail properties within each retail segment. There were more than 200,000 retail properties registered at the Dutch

⁹A table showing all 14 3-digit SBI classification codes and the corresponding retail segments can be found in Appendix 2.A.

¹⁰The all-parcel file, i.e. the *Administration of Buildings and Addresses (BAG)* dataset, incorporates the geo-location information of every building in the Netherlands.

Figure 2.2: Locations of newly-opened and existing stores in the retail segment ‘Retail Sale in Non-Specialized Stores’

Note: This figure shows the locations of newly-opened and existing stores in the ‘Retail sale in non-specialized stores’ segment as an example. The blue dots represent stores that existed throughout the entire 2008 to 2011 period and the red crosses represents stores that opened between 2009 and 2011.

Chamber of Commerce in 2011. There are also large differences between retail segments. The ‘Shops selling other goods’¹¹ retail segment has the most retail properties (44,166) and accounts for about 22% of all retail properties. The ‘Hairdressing and beauty treatment’ segment has the second highest number of retail properties. The segment with the least number of retail properties is ‘Tourist information and reservation services’ with fewer than 1,000 retail properties in the entire country.

¹¹This retail segment mainly includes clothing stores, drugstores, and jewelry stores.

As introduced earlier, the second issue I look into is whether the location patterns of newly-opened and existing stores differ. In order to sample sufficient newly-opened stores, I extend the observation period from a single year to the period from 2008 to 2011. I classify stores that are in operation throughout the whole period from 2008 to 2011 as existing stores. Stores that were not present in 2008 but appear in later datasets are regarded as newly-opened stores. Thus my sample includes stores that opened between 2009 and 2011. As an example, Figure 2.2 shows the locations of newly-opened and existing stores in the 'Retail sale in non-specialized stores' segment. The blue dots represent existing stores and the red crosses the newly-opened ones.

Table 2.2 shows the summary statistics for the newly-opened and existing stores from 2008 to 2011. As in the 2011 analysis of segments, the 'Shops Selling Other Goods' and 'Hairdressing and Beauty Treatment' segments have the most retail properties. However, in terms of new stores it is the 'Retail Sale not via Stores and Markets' segment that has the largest number of newly-opened stores at 15,481 and accounts for 22.53% of the total number of newly-opened stores from 2009 to 2011. This can be seen as reflecting the rapid development of e-commerce in the Netherlands.

To explore the gendered distribution of employment, I use the 2011 LISA dataset again. Table 2.3 presents the summary statistics of male and female employees in each retail segment. First, in terms of employment more generally, it is noteworthy that although the 'Hairdressing and Beauty Treatment' segment accounts for about 20% of the total number of retail properties, it provides less than 7% of the total number of jobs. Conversely, the 'Retail Sale in Non-Specialized Stores' segment provides more than 23% of all retail jobs in less than 3% of all retail properties. The segment with the largest number of male employees is 'Retail Sale in Non-Specialized Stores' that accounts for nearly one-quarter of all male retail employees. The 'Shops selling Other Goods' segment is the largest employer of females, accounting for just over one-quarter of all female retail employees.

Table 2.2: Summary statistics of newly-opened and existing retail properties within each retail segment

	Newly-opened		Existing		All	
	Number	Percentage	Number	Percentage	Number	Percentage
Retail sale in non-specialised stores	1,284	1.87%	5,175	3.61%	6,459	3.05%
Specialised shops selling food and beverages	2,591	3.77%	10,689	7.46%	13,280	6.26%
Petrol stations	259	0.38%	1,842	1.29%	2,101	0.99%
Shops selling consumer electronics	1,176	1.71%	2,990	2.09%	4,166	1.97%
Shops selling other household equipment	3,996	5.82%	11,817	8.25%	15,813	7.46%
Shops selling reading, sports, camping and recreation goods	2,158	3.14%	6,877	4.8%	9,035	4.26%
Shops selling other goods	11,902	17.32%	35,266	24.62%	47,168	22.25%
Market sale	3,831	5.57%	6,355	4.44%	10,186	4.81%
Retail sale not via stores and markets	15,481	22.53%	6,318	4.41%	21,799	10.28%
Restaurants	6,301	9.17%	17,579	12.27%	23,880	11.27%
Bars	2,265	3.3%	8,656	6.04%	10,921	5.15%
Travel agencies and tour operators	1,564	2.28%	2,488	1.74%	4,052	1.91%
Tourist information and reservation services	597	0.87%	412	0.29%	1,009	0.48%
Hairdressing and beauty treatment	15,313	22.28%	26,790	18.7%	42,103	19.86%
Total	68,718	100%	143,254	100%	211,972	100%

Note: This table presents the summary statistics of retail segments including the number of retail properties and the percentage of outlets in each segment.

Table 2.3: Summary statistics of male and female employees within each retail segment

	Male		Female		All	
	Number	Percentage	Number	Percentage	Number	Percentage
Retail sale in non-specialised stores	99,856	23.64%	135,404	23.08%	235,260	23.32%
Specialised shops selling food and beverages	22,437	5.31%	33,306	5.68%	55,743	5.52%
Petrol stations	6,652	1.58%	6,754	1.15%	13,406	1.33%
Shops selling consumer electronics	13,263	3.14%	4,226	0.72%	17,489	1.73%
Shops selling other household equipment	45,008	10.66%	37,395	6.37%	82,403	8.17%
Shops selling reading, sports, camping and recreation goods	18,128	4.29%	17,148	2.92%	35,276	3.50%
Shops selling other goods	54,925	13.00%	149,079	25.41%	204,004	20.22%
Market sale	10,468	2.48%	6,525	1.11%	16,993	1.68%
Retail sale not via stores and markets	19,799	4.69%	14,682	2.50%	34,481	3.42%
Restaurants	87,397	20.69%	82,136	14.00%	169,533	16.80%
Bars	30,415	7.20%	28,356	4.83%	58,771	5.82%
Travel agencies and tour operators	4,744	1.12%	9,463	1.61%	14,207	1.41%
Tourist information and reservation services	1,555	0.37%	2,256	0.38%	3,811	0.38%
Hairdressing and beauty treatment	7,702	1.82%	59,869	10.21%	67,571	6.70%
Total	422,349	100.00%	586,599	100.00%	1,008,948	100.00%

Note: This table presents the summary statistics for retail segments including the number of employees and the percentage of employees in each segment.

2.4 Methodology

The main aim of this paper is to explore the location patterns of retail properties in the various retail segments. To achieve this, I use the distance-based methodology that was created by Duranton & Overman (2005) and further developed by themselves Duranton & Overman (2008) and by Billings & Johnson (2012). The idea behind this methodology is to compare the distribution of pairwise distances of properties in the same retail segment to the distribution of pairwise distances of all possible properties in the retail sector. There are three steps in applying this methodology. First, one has to select relevant properties in the segment. Next, calculate the distances between every two identified properties and estimate the distribution of the pairwise distances using a kernel function. The final step is to construct counterfactuals and compare the distributions of the pairwise distances of chosen properties with those of the counterfactuals.

Compared to other methodologies, the Duranton & Overman (2005) method has two main advantages. First, it is not sensitive to geographical scale and spatial concentration. While other methodologies are usually restricted to a chosen geographical scale, the Duranton & Overman (2005) approach uses the distance between every two establishments and is thus unaffected by geographical scale. Second, through the use of constructed counterfactuals, it is possible to calculate global confidence intervals based on Monte Carlo simulations. With all the registered retail properties in the Netherlands, we know all the possible location choices of retailers.¹² For each retail segment, we can construct a hypothetical segment, i.e. the counterfactual, by selecting the same number of retail properties randomly from all the registered retail properties. By definition, this hypothetical segment should have the same potential location choices as the actual one. The distribution of the pairwise distances of properties in this hypothetical segment can also be calculated. We then can use Monte Carlo simulations to repeat this procedure to obtain the confidence intervals of the distribution of the retail segment.

The core of the Duranton & Overman (2005) method is the estimation of the dis-

¹²In the Netherlands, it is rather difficult to change the function of real estate properties or develop new retail properties because of strict land use policy. Thus, the number of retail properties can be seen as fixed in a short period of time.

tribution of pairwise distances. For a segment with n properties, there are $\frac{n(n-1)}{2}$ unique pairwise distances. The distribution of pairwise distances between n establishments is the summation of $\frac{n(n-1)}{2}$ kernel functions, which can be written as

$$\hat{K}(d) = \frac{1}{n(n-1)h} \sum_{i=1}^{n-1} \sum_{j=i+1}^n f\left(\frac{d - d_{ij}}{h}\right), \quad (2.1)$$

where $\hat{K}(d)$ is the estimator of the density of pairwise distances at any distance d ; d_{ij} is the Euclidean distance between establishments i and j ; h is the bandwidth¹³; and $f(\cdot)$ is a Gaussian kernel function.¹⁴

Equation (2.1) can be used directly to answer the first question of this paper by estimating the distribution of pairwise distances between retail properties within each retail segment. To complete the method, the final step is to construct counterfactuals and compare the actual distribution of distances to the distribution of randomly generated counterfactuals. For this, I randomly choose an equal number of establishments from all the retail properties in the Netherlands as counterfactuals. It is then possible to obtain global confidence intervals for each retail segment using Monte Carlo simulations.¹⁵

The second issue investigated in this paper is whether newly-opened stores are located differently than existing stores. To do this, I compare the distribution of pairwise distances between newly-opened and existing stores and the distribution of pairwise distances between existing stores. Supposing that there are n newly-opened stores and m existing stores, there are in total nm unique pairwise distances. As such, Equation (2.1) can be rewritten as

$$\hat{K}_{nm}(d) = \frac{1}{nmh} \sum_{i=1}^n \sum_{j=1}^m f\left(\frac{d - d_{ij}}{h}\right). \quad (2.2)$$

The construction of counterfactuals is more complicated in this case because, when constructing counterfactuals for each retail segment, it is essential to keep the pro-

¹³In setting the bandwidth, I follow the standard approach adopted by Duranton & Overman (2005), which is to use the optimal bandwidth as proposed by Silverman (1986).

¹⁴When the distance is very small, the corresponding kernel density may be negative and, to avoid this, I adopt the reflection method proposed by Silverman (1986).

¹⁵For each retail segment, 1000 Monte Carlo simulations were performed.

portions of newly-opened and existing stores constant. Therefore, to construct such counterfactuals, I first draw randomly the same number of properties of each retail segment from all the registered retail properties in the Netherlands. I then draw the same number of newly-opened stores within each retail segment from all the randomly chosen retail properties in this segment. In this way can I keep the proportions of newly-opened and existing stores constant. Besides, in the hypothetical segments constructed in this way, newly-opened and existing stores are distributed no-differently.

Equation (2.1) and (2.2) are both designed for property-level data. To investigate the gendered distribution of employment it is necessary to instead take employees as the unit of observation. What then has to be considered is the pairwise distances between all pairs of employees belonging to different establishments. In this case, the density estimator becomes:

$$\hat{K}_{emp} = \frac{1}{\sum_{i=1}^{n-1} \sum_{j=i+1}^n e(i)e(j)h} \sum_{i=1}^{n-1} \sum_{j=i+1}^n e(i)e(j)f\left(\frac{d - d_{ij}}{h}\right), \quad (2.3)$$

where $e(i)$ and $e(j)$ denote the number of employees of establishment i and j respectively.

2.5 Results

2.5.1 Location patterns of retail segments

Figure 2.3 plots the location patterns for each retail segment in the Netherlands. The solid blue line in the figure represents the kernel density function, i.e. the location pattern, of each retail segment. Here, the kernel density functions are estimated using Equation (2.1). The horizontal axis covers distances from 0 to 120 kilometers, while the vertical axis is the kernel density.¹⁶ The two dashed lines in the figure represent the global confidence interval at the 95% confidence level. Graphically, a clustered pattern is identified when the actual kernel density is above the upper con-

¹⁶Duranton & Overman (2005) choose a median distance of 180 km between all pairs of establishments as their threshold. Here, I follow their method but choose a median distance of 120 km as the threshold for the Dutch retail sector.

fidence interval, and a dispersed pattern is detected if the actual kernel density lies below the lower confidence interval. As most retailers will only give consideration to other retailers within a relatively short distance when making location choices, the discussion here focuses on the kernel density function within a short distance.¹⁷ As most retailers will only give consideration to other retailers within a relatively short distance when making location choices, the discussion here focuses on the kernel density function within a short distance.

Based on Figure 2.3, we can categorize the 14 retail segments into three groups based on their location patterns. The first group includes five retail segments that are more clustered than the distribution pattern of the entire retail sector: ‘Specialized Shops Selling Food and Beverages’ (SBI 472), ‘Restaurants’ (SBI 561), ‘Bars’ (SBI 563), ‘Travel Agencies and Tour Operators’ (SBI 791), and ‘Tourist Information and Reservation Services’ (SBI 799). It can be argued that ‘Specialized Shops Selling Food and Beverages’ generally require a large customer base and that small specialized stores in particular rely on the additional footfall that is generated by other retailers (Ingene & Ghosh, 1990; Yeates et al., 2001; Burger et al., 2014; Koster et al., 2019; Zhang et al., 2020b). It can also be argued that Restaurants, Bars, Travel Agencies and Tour Operators, and Tourist Information and Reservation Services provide customers with heterogeneous services and so are not that sensitive to the competition provided by other retailers within the same segment. One can thus see why retailers from these five segments might profit from the clustering of retail properties, and thus, as the analysis shows, are indeed more clustered than the retail sector as a whole.

The second group includes five segments that are more dispersed than the overall retail sector. This group consists of ‘Retail Sale in Non-Specialized Stores’ (SBI 471), ‘Petrol Stations’ (SBI 473), ‘Shops Selling Consumer Electronics’ (SBI 474), ‘Shops Selling Reading, Sports, Camping and Recreation goods’ (SBI 476), and ‘Hairdressing and Beauty Treatment’ (SBI 960). All these segments show a more dispersed location pattern than the overall retail sector within a distance range from 0 to 20 kilometers. It can be argued that this is because these segments provide goods and services that are homogeneous in terms of quality and price. The products and ser-

¹⁷One limitation to this and all other approaches is that non-random patterns will not be detected if they do not involve concentration or dispersion.

Figure 2.3: Kernel density functions of 14 retail segments in the Netherlands

vices provided in these segments can easily be replaced by another retailer from the same segment. It makes little difference to consumers which retailer they use within

Figure 2.3: Kernel density functions of 14 retail segments in the Netherlands (Continued)

Note: This figure presents the Kernel density function of pairwise distances between retail properties for 14 retail segments. The retail segments are classified using three-digit SBI sector classification codes. The solid blue line in the figure represents the kernel density function for each retail segment, while the dashed line represents the global confidence intervals based on a random selection from the entire retail sector.

these segments. As a result, retailers within these segments will tend to locate away from similar retailers to avoid loss through competition.

The third group includes those segments whose distribution patterns are similar to the distribution pattern of the entire retail sector: 'Shops Selling Other Household

Equipment' (SBI 475), 'Shops selling other goods' (SBI 477), and 'Retail Sale not via Stores and Markets' (SBI 479). Contrary to my expectations, some segments that provide heterogeneous products, such as clothing stores and furniture stores, are in this group. However, this does not necessarily mean the clothing stores or furniture stores are not more clustered or dispersed. Compared with the segments in the first two groups, these three segments each include a much more diverse range of stores so it is not altogether surprising that their distribution patterns are very similar to that of the entire retail sector.

2.5.2 Location patterns of newly-opened and existing stores

Figure 2.4 presents the kernel density functions for pairwise distances between newly-opened and existing stores and between two existing stores. The kernel density function of newly-opened to existing stores is estimated using Equation (2.2) and the kernel density function for pairs of existing stores is estimated using Equation (2.1). The solid blue lines are the kernel density functions for pairs of existing stores and the solid red lines the kernel density functions for newly-opened to existing stores. Since 'existing stores' are those that were present during the whole period from 2008 to 2011, it is not surprising that the blue lines are very similar to those in Figure 2.3 - both using 2011 data only.

By comparing the kernel density functions of newly-opened to existing stores with those of pairs of existing stores, we can assess whether a retail segment is becoming more or less clustered. The only segment showing a tendency towards becoming more clustered is 'Petrol Stations'. There are four segments ('Specialized shops selling food and beverages', 'Shops selling other goods', 'Market sale', and 'Hairdressing and beauty treatment') that shows no signs of becoming either more or less clustered, at least over short distances. This is reflected in the way the blue and red lines of these segments lie very close to each other in the left hand parts of the segment plots in Figure 2.4. For other segments, the figure shows that newly-opened stores would seem to look for sites that are not too close to existing stores. For example, the red line for the 'Retail Sale in Non-Specialized stores' segment is clearly below the blue line for distances up to about 15 kilometers. This is in line

Figure 2.4: Kernel density functions of pairwise distances from newly-opened stores to existing stores and pairwise distances between existing stores

Figure 2.4: Kernel density functions of pairwise distances from newly-opened stores to existing stores and pairwise distances between existing stores (Continued)

Note: This figure presents the Kernel density functions of pairwise distances from newly-opened stores to existing stores and pairwise distances between exiting stores. The blue line shows the kernel density function between existing stores, while the red line shows the kernel density function of newly-opened stores to existing stores.

with the findings of Zhou & Clapp (2015).

2.5.3 Location patterns of male and female employees in the Dutch retail sector

In the previous sections, establishment-level data have been used to estimate kernel density functions. However, this distribution of retail properties does not represent the distribution of employment in this sector since employees are very unevenly distributed across retail establishments. In order to gain insight into the location patterns of employees in the Dutch retail sector, I make use of the employment data available for each outlet and use Equation (2.3) to analyze the pairwise distances between all pairs of employees working at different establishments. Further, I separate employees based on gender to see if the location patterns in each retail segment have similar gendered dimensions.

Figure 2.5 shows the Kernel density functions of pairwise distances between male employees and pairwise distances between female employees in each retail segment. The blue line shows the kernel density function of male employees, while the red line shows the kernel density function of female employees. As in the previous reflections, I still focus on the distributions over short distances. There are only five segments ('Retail sale in non-specialized stores', 'Petrol stations', 'Shops selling consumer electronics', 'Retail sale not via stores and markets', 'Shops selling other household equipment') that show no sign of different distribution patterns of male and female employees. In all the other segments, we can observe that the distribution of male employees is more clustered than that of female employees over short distances.

Figure 2.5: Kernel density function of male and female employees in each retail segment

Figure 2.5: Kernel density function of male and female employees in each retail segment (Continued)

Note: This figure presents the Kernel density functions of pairwise distances between male employees and pairwise distances between female employees in each retail segment. The blue line shows the kernel density function of male employees, while the red line shows the kernel density function of female employees.

2.6 Conclusion

This paper explores the location patterns of retail properties for different retail segments in the Netherlands. It is widely observed that the retail sector has a tendency to cluster. However, one might expect different retail segments to have different preferences when it comes to clustering. To identify the location patterns of the various retail segments, I use a distance-based methodology to estimate the kernel density function of retail properties in each segment. I investigate 14 retail segments, with a combined total of more than 200,000 retail properties, and focus on three issues.

First, I compare the location patterns of retail properties in each retail segment and concluded that those retail segments that provide specialized and heterogeneous goods and services are more clustered, whereas those that provide homogeneous goods and services are more dispersed. Second, I looked into the location patterns of newly-opened stores compared with existing stores. I compared the distributions of pairwise distances from newly-opened stores to existing stores with the pairwise distances between pairs of existing stores. This identified that, for most retail segments, newly-opened stores are more dispersed than existing stores. Third, I examined location patterns of employment in the retail sector in the Netherlands, and particularly investigated the distributions of male employees and of female employees separately. This showed that, in most retail segments, male employees are more clustered than female employees over short distances.

In this paper, the analysis divided the retail sector into 14 retail segments based on 3-digit SBI classification codes. However, some of the segments contain very diverse economic activities which could explain why they have a location pattern that is very similar to that of the overall Dutch retail sector. To investigate the actual location pattern of certain types of stores, such as the clothing and furniture outlets, a more refined classification needs to be adopted in future research.

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Chapter 3

Tenant Mix and Retail Rents in High Street Shopping Districts

Abstract

Urban areas have long had shopping districts in which retail properties are concentrated. It is argued that the diversity of retail tenants, often called tenant mix, contributes to the image and attractiveness of the high street shopping district. These districts are characterized by fragmented ownership and therefore the tenant mix is outside the control of individual property investors. We aim to explore the relationship between tenant mix and retail rents by studying high street shopping districts in the Netherlands. We start with delineating high street shopping districts using granular data on the spatial distribution of retail jobs. Within each shopping district, tenant mix is measured using detailed information on SBI sector classification and the number of retail properties. We find shopping districts with greater tenant mix show higher retail rents compared to districts with lower tenant mix.

Keywords: *Tenant mix, shopping externalities, high street retail, difference-in-difference*

3.1 Introduction

Shopping districts are prevalent in urban areas. Shopping districts are areas where retail properties and retail activities concentrate. The diversity of retail tenants in a shopping district is called tenant mix and it determines the variety of goods and services that a shopping district can provide to consumers. It is well known in the retail industry that tenant mix is an important factor which contributes to the image and attractiveness of a shopping district.

Tenant mix of a shopping district is important to consumers because they prefer a shopping district with a wide variety of goods and services, relative to one with less variety (Glaeser et al., 2001). By visiting shopping districts that provide various goods and services, consumers have more choices and they can save on out-of-pocket costs and time costs (Stahl, 1982; Claycombe, 1991; Brueckner, 1993; Teller & Reutterer, 2008). Tenant mix is also important to retail tenants, because of the existence of shopping externalities (Brueckner, 1993; Wheaton, 2000; Koster et al., 2014). A retail tenant may benefit from footfall, i.e. number of visitors, brought about by other retail tenants in their proximity. For example, a café on the corner benefits from nearby shops in the same shopping district, as consumers who just finished shopping may stop by for a drink. This shopping externality is especially important for small retail tenants because they greatly rely on footfall generated by other, especially anchor, retail tenants (Benjamin et al., 1992; Brueckner, 1993; Gatzlaff et al., 1994; Miceli & Sirmans, 1995; Colwell & Munneke, 1998; Pashigian & Gould, 1998). If tenant mix affects the image and attractiveness of shopping districts, it is likely that this is capitalized into retail rents (Pashigian & Gould, 1998; Cho & Shilling, 2007; Arzaghi & Henderson, 2008; Ahlfeldt et al., 2015).

Most existing papers on the relationship between tenant mix and retail rents consider shopping malls (Eaton & Lipsey, 1982; Abratt et al., 1985; Sirmans & Guidry, 1993; Gerbich, 1998; François et al., 2005; Des Rosiers et al., 2009; Yuo et al., 2011). In shopping malls, property investors control both tenant mix and rents simultaneously, resulting in tenant mix being endogenous by nature. The owner of a shopping mall manages each unit and chooses the optimal tenant mix by distributing units and space to tenants to maximize expected returns of the mall (Gould et al., 2005;

Des Rosiers et al., 2009; Yuo et al., 2011). This is very different from the situation in high street shopping districts. In high street shopping districts, ownership of retail properties is usually fragmented so that tenant mix is exogenous to individual property investors. At the same time, tenant mix is also exogenous to retail tenants. In high street shopping districts, tenant mix largely predates any tenant's decision to rent a retail property, so it cannot have been influenced by determination or negotiation over the retail rents. High street shopping districts provide a useful context to address the relationship between tenant mix and retail rents.

Relative few studies consider retail rents in high street shopping districts. Koster et al. (2019) examine the relationship between footfall and retail rents for high street retail. While they use a clever identification strategy based on spatial variation in footfall, the strategy is essentially based on cross-sectional variation in footfall to time-varying rents. Also, they base their analysis on a limited footfall dataset which is only collected twice-a-year for a couple of hours. Teulings et al. (2018) investigate the land use structure in shopping districts and find a distance decay in retail rents from the center of a shopping district. However, the shopping districts that they use were based on the government's land use plan, and thus time invariant, which may not reflect the real and dynamic concentration of retail properties.

Motivated by the above concerns, we examine the relationship between tenant mix and rents for high street shopping districts. One key challenge in our analysis is to identify geographic areas that precisely reflect shopping district boundaries, shapes and sizes, in order to measure the tenant mix within each shopping district. Shopping districts do not necessarily follow boundaries, shapes and sizes of intended land use designations, which may introduce measurement error by incorrectly assigning a retail property as being inside or outside a particular district (for similar discussions for enterprise zones, see Neumark & Kolko, 2010). To construct accurate shopping districts, we utilize granular data of all retail properties registered at the Dutch Chambers of Commerce. This dataset is collected on a yearly basis, and it comprises information about every retail property's address, SBI sector classification¹⁸, and number of jobs. For every year between 1996 and 2011, we define grids

¹⁸SBI sector classification is a hierarchical classification of economic activities that CBS (*Statistics Netherlands*) uses to classify business units according to their main activity, like NAICS for the U.S. For more information about SBI sector classification, see <https://www.cbs.nl/en-gb/our->

and calculate the density of retail properties for each grid. Adjacent grids are merged to form a cluster if the retail property density of each grid exceeds a threshold. This results in a large number of shopping districts and information about the development of those shopping districts - in terms of boundary, shape, size, number of retail properties and number of jobs - between 1996 and 2011.

For each shopping district, we calculate the tenant mix by using the SBI sector classification and number of retail properties in each classification. We analyze the relationship between tenant mix and retail rents by combining this with data containing information on 6,864 retail rental transactions in the Netherlands between 1996 and 2011. For each of the rental transactions we can identify at any given year whether a retail property falls within a shopping district. Our analysis starts with investigating the functional form of the relationship between retail rents and tenant mix, while controlling for observed heterogeneity. We analyze both linear and semiparametric functional forms to elicit the relationship between tenant mix and retail rents. Next, we estimate a difference-in-difference model to test for unobserved heterogeneity in retail rents. We will show that the heterogeneity in retail rents are largely explained by the variation in the tenant mix of shopping districts.

Our paper extends the literature in several ways. First, we contribute to the literature on the relationship between tenant mix and retail rents. While the role of tenant mix in determining rents has been noticed long before, most existing literature examines shopping malls. We examine the relationship by considering high street shopping districts in the Netherlands. Second, we contribute to the literature of shopping districts using granular data on retail properties. We exploit information on SBI sector classification to distinguish retail activities. This study is one of the first papers to measure the dynamics of tenant mix in this manner, which connects to the literature on agglomeration and coagglomeration economies. We complement information on shopping districts with data on retail rents in the Netherlands and show that retail tenants do not only benefit from the agglomeration of shops, but also that tenant mix in such agglomerations is an important driver explaining retail rents. Third, our findings have important practical implications for shopping districts. We pro-

vide empirical evidence showing that tenant mix is positively related to retail rents, and that shopping districts' variety of goods and services is capitalized into retail rents. To increase the tenant mix of a shopping district may be an effective way to improve the attractiveness of the shopping district and thus to elevate consumers, retail tenants and investors' benefits.

The paper is organized as follows. Section 3.2 discusses the relationship between tenant mix and rents. Section 3.3 describes the data used in our empirical research. Section 3.4 presents the empirical model and Section 3.5 presents baseline regression results. In Section 3.6, we provide a series of sensitivity analyses. Section 3.7 provides a conclusion.

3.2 Retail in shopping districts

3.2.1 Retail market

The retail market we consider is part of an urban economy in which retail properties are unevenly distributed across space as they concentrate in shopping districts. We assume that in each shopping district there are two types of agents, namely retail property investors and retail tenants. Retail property investors own retail properties while retail tenants rent properties from investors. Retail tenants provide various goods and services to consumers.¹⁹ Both investors and retail tenants can freely enter or exit any of the shopping districts. The retail rental market we consider is competitive.

The theoretical framework we envision is based on a matching function that represents a two-sided search process of investors and tenants.²⁰ Investors with vacant retail properties searching for potential tenants in the same shopping district must use a time-consuming and costly search process, while retail tenants looking for a location must go through a similar process when attempting to find a retail property to be located in. After being matched, retail property investors and retail tenants determine retail rents by Nash bargaining. Upon signing the rental contract, the investor

¹⁹For simplicity, we assume each property investor owns one property only and all retail properties are homogeneous to each other, which will not affect the conclusion.

²⁰A more formal description of the model is relegated to Appendix 3.A.

receives rental income. In the competitive equilibrium state, both retail property investors and retail tenants maximize their profits.

Tenant mix plays an important role in the matching process as it affects the production or turnover of a retail tenant. First, shopping districts with high tenant mix are able to attract more consumers. Consumers generally aim to minimize the costs for their shopping trips. Shopping districts with high tenant mix can reduce consumers' time and transportation costs (Stahl, 1982; Claycombe, 1991; Brueckner, 1993; Teller & Reutterer, 2008) by providing them with a wider variety of goods and services, thus enabling them to complete their shopping within a single shopping trip. When a shopping district has more consumers, the turnover of retail tenants in this shopping district will also be higher. Second, for each retail tenant within a shopping district, they can benefit from the shopping externalities generated by others. Especially for small retail tenants without consumer drawing power, their turnover may depend heavily on the footfall generated by other retail tenants. With higher turnover, retail tenants will be willing to pay higher rents. Meanwhile, from investors' perspective, although individual investors cannot control the tenant mix of a shopping district, they do take tenant mix into consideration when they make decisions whether to buy a property or not. Investors' demand for retail properties located in a shopping district with high tenant mix will push up the cost of owning a property. Consequently, investors will ask for higher rents in return. Pulling these perspectives together, we conjecture that retail rents are positively related to a shopping district's tenant mix.

3.2.2 Retail planning in the Netherlands

Retail land use in the Netherlands is subject to urban planning. The urban planning regulatory framework in the Netherlands includes three levels - national, regional and local - of policy instruments. These interconnected instruments reflect the societal preferences regarding land use and govern local planning decisions. Dutch retail planning has had to adhere to rather restrictive national retail planning regulations. According to national retail planning regulations, retail property is only allowed in designated retail zones (Evers, 2002).

National retail planning in the Netherlands liberalized since 2004. Regional planning authorities responded by reinstalling the main restrictive elements of the previous national retail planning model at the regional level (Van der Krabben, 2009). While retail planning in the Netherlands is implemented at the local level, development of new retail properties must align and comply with regional planning rules. Also, development of new retail properties outside existing retail zones typically requires a change in zoning plans which, when compared to observations of shopping districts in many other countries²¹, is rather unlikely (Van der Krabben, 2009; Nozeman & Van der Vlist, 2014). This makes land use rather persistent in the Netherlands.

However, it is noteworthy that designated retail zones reflect only the *intended* retail land use but not the *actual* retail land use. Indeed, they are different from the shopping districts defined in our paper which refer to areas where retail properties actually concentrate. Moreover, shopping districts are not invariable, as development of new retail properties changes the landscape of shopping districts all the time. Therefore, in the next section, we will propose and discuss a method which can reflect the actual retail land use and its development. This enables us to observe changes in the boundaries, shapes and sizes of shopping districts in the Netherlands.

3.3 Data

We mainly use two datasets for our empirical analysis in this paper. The first dataset contains granular data of all retail properties registered at the Dutch Chambers of Commerce from 1996 to 2011. This dataset is used to construct shopping districts and calculate tenant mix for each shopping district. The second dataset comprises information of retail rental transactions in the Netherlands, also from 1996 to 2011. These rental transactions are matched with shopping districts, based on their transaction year and geographical location.

²¹For instance, France, Portugal, Spain, Turkey, or the U.S.

3.3.1 Shopping district

Shopping districts are concentrations of retail properties in urban areas. However, the precise boundary of a shopping district is difficult to identify. The existing CBS land use data provide information about designated retail zones, but, as discussed above, they do not reflect the actual retail land use and are not updated to incorporate the most recent development of retail land use. The precise identification of shopping district boundaries, as well as how they change over time, plays a central role in our approach. Therefore, we use Geographical Information System (GIS) techniques to delineate shopping districts boundaries, with the help of granular data for all retail properties registered at the Dutch Chambers of Commerce. The granular data are collected yearly and contain information on each retail property's precise address, SBI sector classification and the number of jobs between 1996 and 2011.

We construct shopping districts, based on the density of retail properties, as follows.²² First, we create grids of 10 by 10 meters for the whole Netherlands. Next, for each grid, we calculate the density of retail properties within 100 meters of the grid by using the method of kernel density. When calculating the density, we take the number of jobs at each retail property as the weight for each property.²³ Finally, we choose a predetermined threshold of density and merge adjacent grids with density exceeding this threshold²⁴ to create a shopping district. We apply this procedure to construct shopping districts for every year between 1996 and 2011. Appendix 3.B gives more details about how we construct shopping districts. Figure 3.1 shows the constructed inner-city shopping district of Groningen in 2011 as an example.

²²This methodology is commonly used in applied geography, and has been used to delineate, for example, retail site location selections (Roig-Tierno et al., 2013), retail center attractiveness and catchment areas (Dolega et al., 2016), and retail clusters (Lloyd & Cheshire, 2017; Teulings et al., 2018). Other applications outside retail market analysis include delineation of nature (Daams et al., 2016) and office clusters (Van der Vlist et al., 2019).

²³The choice of using number of jobs as the weight of each retail property has practical reasons. We experimented both with the weights and without the weights. When no weights are used, grids located at the edge of a shopping district usually have a low density value, which makes the shopping districts constructed smaller than their actual size. This has serious consequences in the later stage of our empirical analysis, because retail properties at the edge of a shopping district are often excluded from the corresponding shopping district. However, when the weights are used, this problem is relieved.

²⁴We set this threshold of density to be 3,421 jobs per km^2 , which is equivalent to the 65th percentile of the retail property density in 2010. which is equivalent to the 65th percentile of the retail property density in 2010. We made our choice of this threshold based on the entire distribution of retail property density and our various experiments. Changing the threshold of density is part of our sensitivity analysis.

Figure 3.1: An example of shopping districts constructed based on retail property densities

Note: This figure shows the inner-city shopping district in the city of Groningen in 2011. The blue area represents the shopping district. The black dots depict registered retail properties in 2011 and the red triangles are rental transactions in 2011.

After the construction of shopping districts for every year, we calculate the size, number of retail properties and number of jobs for each shopping district. Table 3.1 presents the summary statistics of constructed shopping districts, where at least one rental transaction is observed. The size of these shopping districts ranges from 800

Table 3.1: Summary statistics of shopping districts

	Mean	Std.Dev.	Median	Min	Max
Shopping district size (in 1,000 m^2)	120.240	153.390	81.5	0.8	1,824.9
Number of retail properties in a shopping district	193.745	273.281	110	2	3,235
Number of jobs in a shopping district	1,365.897	2,053.798	761	11	23,295
<i>MIX</i>	22.206	7.540	23.442	1.410	40.806
Number of shopping districts	2,672				

Note: This table presents the summary statistics of shopping districts with at least one rental transaction observed. For each shopping district, we calculate its tenant mix, size, number of retail properties and number of jobs. To be precise, the tenant mix is calculated based on 5-digit SBI sector classification.

m^2 to 1,824,900 m^2 , with a median of 81,500 m^2 . A shopping district contains on average about 194 shops and 1,366 jobs. The minimum number of shops in a shopping district is 2, while the maximum is 3,235. Correspondingly, there are at least 11 jobs and at most 23,295 jobs in a shopping district. This indicates that we capture local neighborhood convenience shopping districts as well as city center shopping districts.²⁵ Additional discussion about the shopping districts can be found in Appendix 3.B.

3.3.2 Tenant mix

The focus of our paper is the relationship between tenant mix and rents in shopping districts. To measure the tenant mix of a shopping district, we rely on the SBI sector classification contained in our granular data. The SBI sector classification code is composed of 2 to 5 digits. Each SBI code represents one classification of retail activity. Fewer digits signifies a more abstract way of classification. The 5-digit SBI code, which is the most detailed classification, is used in our analysis.²⁶ The tenant mix of a shopping district j in year t is defined as follows:

$$MIX_{jt} = \frac{1}{\sum_{l=1}^m \left(\frac{B_{ljt}}{B_{jt}} \right)^2}, \quad (3.1)$$

²⁵For a retail industry classification for shopping districts, see <https://locatus.com/wp-content/uploads/2016/07/Shopping-area-classification.pdf>

²⁶We also experiment to calculate the tenant mix using 3-digit and 4-digit SBI sector classification codes and apply them in the next empirical analysis. The results are similar and our main conclusion remains unchanged.

where B_{ljt} is the number of retail properties of SBI sector classification l in shopping district j in year t and B_{jt} is the total number of retail properties in shopping district j in year t ; m is the number of SBI sector classifications in shopping district j in year t . Our tenant mix is actually the *reciprocal* of the well-known Herfindahl Index.²⁷ Note that MIX_{jt} cannot be smaller than 1. When MIX_{jt} equals 1, it means all retail properties in shopping district j are of the same SBI sector classification. MIX_{jt} increases when retail activities in shopping district j become more diverse. Table 3.1 shows that the mean of MIX_j is 22.206, the median is 23.442 and the standard deviation is 7.540 for the shopping districts in which we observe at least one rental transaction. The maximum of MIX_{jt} is 40.806, which represents the most diverse shopping district. The minimum of MIX_{jt} is 1.410, which means almost no diversity.

3.3.3 Retail rents

Our dataset of retail rents comes from Strabo, a consulting firm that conducts market research and collects commercial property data. The Strabo dataset contains 9,436 rental transactions for the Dutch retail market from 1996 to 2011. It provides detailed information about rental transactions, including annual rent, property size, precise location, name of the tenant and year of transaction. We use the precise location to map rental transactions to the all-parcel file. The all-parcel file, *Administration of Buildings and Addresses (BAG) dataset*, provides information on the building year and geo-location of every building in the Netherlands. Based on geo-location, we then match all rental transactions with the shopping districts in the corresponding year. There are 6,864 rental transactions that are located in a shopping district at the time of being transacted. So for each rental transaction incorporated in a shopping district, we have detailed information on their retail rents, property characteristics, and corresponding shopping district characteristics, all measured at the year when the rental transaction happened. Figure 3.2 maps the location of retail properties registered at the Dutch Chamber of Commerce and rental transactions by taking year 2011 as an example. Black dots represent all retail properties registered at the Dutch Chambers of Commerce in 2011 and red triangles represent all rental transactions in

²⁷The Herfindahl Index has been previously used to measure tenant mix. See, e.g., Des Rosiers et al. (2009) and Ambrose et al. (2018).

Figure 3.2: Location of retail properties and rental transactions in the Netherlands, 2011

Note: This figure shows the location of retail properties registered at the Dutch Chamber of Commerce and rental transactions, taking year 2011 as an example. Black dots represent all retail properties registered at the Dutch Chambers of Commerce in 2011 and red triangles represent all rental transactions in 2011.

2011.²⁸

Table 3.2 presents descriptive statistics for rental transactions located in a shopping district. The average annual rent for a retail property is about 50,071 euros. The average annual rent per m^2 is about 291 euros. Annual rents vary between 15 and 2,351 euros per m^2 . Most retail properties with the lowest rents per m^2 refer to retail properties in small cities and transacted in the late 1990s. Retail properties with the highest rent per m^2 are usually located in very popular streets, such as Kalverstraat, Amsterdam. Since rental transactions are matched with shopping districts, we gain

²⁸For further details about data management, see Appendix 3.B.

Table 3.2: Summary statistics of rental transactions

	Mean	Std. Dev.	Median	Min	Max
Rent price	50,070.950	40,933.820	36,529	9,000	338,380
Rent price per m^2	291.4081	201.1645	238	15	2,351
<i>MIX</i>	22.368	6.077	22.798	1.410	40.806
Property size (m^2)	225.527	248.462	155	20	4,200
Transaction year	2003.627	4.428	2004	1996	2011
Average income per resident (in 1,000 euros)	15.690	5.610	14	0	43.6
Population density per km^2	6,036.453	3,501.559	5,419	2	28,060
Distance to train station (m)	1,872.436	3,038.740	846.038	27.268	22,766.360
Distance to water body (m)	225.362	169.818	184.647	2.265	1,180.464
Chain (1=yes)	0.396				
Corner (1=yes)	0.179				
Located in a shopping mall (1=yes)	0.212				
Building status					
Existing (1=yes)	0.933				
New (1=yes)	0.049				
Renovated (1=yes)	0.018				
Building periods					
<1945	0.422				
1945-1960	0.100				
1961-1970	0.049				
1971-1980	0.069				
1981-1990	0.050				
1991-2000	0.108				
>2000	0.203				
Number of rental transactions	6,864				

Note: Table 3.2 presents summary statistics for rental transactions located in a shopping district when they are transacted. Distance to train station and to water body is computed using GIS techniques. Chain = 1 if any retail tenants rent and operate at multiple retail properties. Corner = 1 if a retail property is located within 15 meters of an intersection of streets. Building period is obtained from BAG. Neighborhood characteristics are acquired from CBS neighborhood statistics.

tenant mix for every rental transaction. The mean of the tenant mix is 22.368 and the standard error is 6.077.

Table 3.2 provides also information on structural characteristics of these retail properties. The average size of 226 square meters reflects the small size of many high street retail properties in the Netherlands. About 40% of the tenants of rental

transactions belong to a retail chain.²⁹ About 21% of the rental transactions refer to retail properties located in inner-city shopping malls relative to street shops.³⁰ About 18% of the retail properties are located at the corner of a street.³¹ We also compute the distance between a retail property to the nearest train station, as well as the distance between it and the nearest water body. The average distance to the nearest train station is about 1,872 meters, and the average distance to the nearest water body is about 225 meters. Furthermore, 4.9% of the properties are newly built when transacted, while 1.8% are just renovated. In total, 42% of the properties are built before 1945, 38% between 1945 and 2000, and 20% after 2000. The distribution of building periods in our sample reflects the historical footprint of retail planning in the Netherlands.

We also gather information on neighborhood characteristics for our rental transactions by matching rental transactions with CBS neighborhood statistics. Neighborhood characteristics capture part of the location effects on retail rents. As we can see in Table 3.2, the average income per resident in the neighborhood is about 15,690 euros annually. The average population density of the neighborhood is about 6,036 per km^2 .

3.4 Empirical model

3.4.1 Functional form

The aim of our paper is to investigate the relationship between tenant mix and rents. We start investigating the functional form with a standard hedonic price model where we include retail rents as the dependent variable and tenant mix as the independent key variable, controlling for other variables that may have an impact on retail rents. Let R_{ijt} represent the rent of a retail property i located at shopping dis-

²⁹For any retail tenants who rent and operate at multiple retail properties, we define them as a retail chain. It can refer to not just shops but also restaurants or any other types of retail tenants.

³⁰In the Netherlands, shopping malls are usually located on high streets in cities, which means many shopping malls are contained in shopping districts. For an example, see Shopping Centre Magna Plaza Amsterdam. <https://www.magnaplaza.nl/>.

³¹We set Corner = 1 if a retail property is located within 15 meters of an intersection of streets.

trict j in year t . Our empirical model is formulated as follows:

$$\log(R_{ijt}) = \alpha + \beta MIX_{jt} + \theta C_{it} + \phi X_{it} + \gamma_t + \mu_j + \epsilon_{ijt}, \quad (3.2)$$

where MIX_{jt} is the tenant mix of a shopping district j in year t ; C_{it} is a vector consisting of the number of retail properties in different SBI sector classifications within a buffer of property i in year t ; X_{it} is a vector of control variables of retail property i in year t which include property, shopping district and location characteristics; γ_t and μ_j are year and location fixed effects; ϵ_{ijt} is an i.i.d. error term; and $\alpha, \beta, \theta, \phi, \gamma_t$ and μ_j are the parameters to be estimated. C_{it} is used to capture the competition that a retail tenant faces in the proximity of the property. We assume the radius of the buffer that we used to calculate C_{it} to be 100 meters, since we think the competition effect is rather local.³²

For retail property characteristics we include property size (in m^2), building period, and an indicator for if the retail property is located in a shopping mall, as owners of shopping malls often for ask higher rents relative to street shops. We also include dummy variables indicating new or just renovated properties because if a property is newly built or has just been renovated, one expects a higher rent for its retail tenant. Furthermore, we include tenant-type controls to capture unobserved differences in retail tenants' behaviors.

Other important determinants of retail rents are location characteristics. First, we include the average income per resident and population density of the neighborhood that a retail property is in, since neighborhood status may impact retail rents. Second, we add the logarithm of the distance between a retail property and its nearest train station, as well as the distance to the nearest water body. If a retail property is close to a train station, it is more accessible to consumers. In the Netherlands, water bodies, such as canals, are hotspots which attract many tourists. The distance to a train station or a water body may have an impact on retail rents. We also include urbanity fixed effects.³³ Last, we include PC4 dummies to control for all time-invariant

³²We tested by changing the buffer radius to be 50 meter and 250 meters. We also tried to calculate the number of retail properties in each SBI sector classification for every shopping district, instead of buffers. None of these effected significant changes to our results.

³³In the Netherlands, every neighborhood is given an urbanity class 1-5 based on its density of addresses. Class 1 represents very high urbanity, which represents more than 2500 addresses per

location characteristics.³⁴

The standard hedonic price model as depicted in Equation (3.2) has some important limitations. One such limitation is that it assumes a linear functional form between retail rents and tenant mix. However, a nonlinear relationship may actually exist between retail rents and tenant mix.³⁵ Because retail rent is a function of numerous characteristics, including many location fixed effects, it would be a tedious task to estimate a fully nonparametric hedonic regression. We therefore propose to use a semiparametric model which does not assume a specific functional form between retail rents and tenant mix. Such a semiparametric model is argued to estimate the hedonic price model more accurately when there are enough data (Sheppard, 1999). Similar semiparametric hedonic regression models can be found in the literature (see, e.g., Bajari & Kahn, 2005; Bin, 2005; Bontemps et al., 2008; Koster & Rouwendal, 2012; Koster et al., 2014). The semiparametric model we propose is as follows:

$$\log(R_{ijt}) = \alpha + \Omega(MIX_{jt}) + \theta C_{it} + \phi X_{it} + \gamma_t + \mu_j + \epsilon_{ijt}, \quad (3.3)$$

where $\Omega(\cdot)$ is a smooth function of tenant mix with a bounded first derivative. Following the method of Yatchew (1997) and Yatchew (1998), we use a differencing method to fit the model. We first sort the data from the smallest to the largest tenant mix. We then take the first difference of Equation (3.3) and estimate the differenced model using OLS.³⁶ These results will provide us with initial evidence of the functional form between retail rents and tenant mix.

*km*². Class 5 represents no urbanity, which represents less than 500 addresses per *km*².

³⁴In the Netherlands, a postcode is a combination of four digits and two letters. The former part, 4 digits, is called PC4 and usually stands for a neighborhood.

³⁵We estimated several different regressions to test for the nonlinear relationship between retail rents and tenant mix. To be specific, we estimated specifications where we included different polynomials. We also estimated a specification where we categorized the tenant mix instead of including the continuous tenant mix variable. The results of these different specifications suggest that the relationship between retail rents and tenant mix may be nonlinear, which gives us more reasons to consider nonparametric estimation methods. These regressions with different specifications can be found in Appendix 3.C.

³⁶We also tried different differencing orders for the semiparametric regression. The results we obtained are quite similar. However, considering using higher order differencing may lead to biased results, we prefer to use the first difference here.

3.4.2 Unobserved heterogeneity

To further explore the relationship between tenant mix and retail rents, we investigate unobserved heterogeneity in retail rents. Whereas in the standard hedonic model we ignored retail properties outside shopping districts, we now include these observations to exploit variation in whether or not a retail property has ever been or will be included in a shopping district.

This addition is made possible by the large number of shopping districts in the Netherlands and access to information about the development of those shopping districts – in terms of boundary, shape and size – between 1996 and 2011. With the availability of such data, we are able to estimate a difference-in-difference model which allows us, contrary to the standard hedonic model, to control for pre-existing differences between retail properties located in shopping districts and those outside (see, e.g., Been et al., 2016; Van Duijn et al., 2016; Van der Vlist et al., 2019). The difference-in-difference model we propose is as follows:

$$\begin{aligned} \log(R_{ijt}) = & \alpha + \tau_1 SD_i + \tau_2 SD_i * S_{it} + \tau_3 SD_i * S_{it} * MIX_{jt} + \\ & + \theta C_{it} + \phi X_{it} + \gamma_t + \mu_j + \epsilon_{ijt}, \end{aligned} \quad (3.4)$$

where SD_i is a dummy variable which equals to 1 if retail property i has ever been or will be included in a shopping district; S_{it} is a dummy variable which equals to 1 if a retail property i is located in a shopping district in its transaction year t .

The difference-in-difference model includes three key variables, SD_i , $SD_i * S_{it}$ and $SD_i * S_{it} * MIX_{jt}$. We use these variables to investigate the heterogeneity in retail rents. SD_i captures the heterogeneity in retail rents between retail properties that are never and never will be in a shopping district and those that have been or will be in a shopping district but are, in transaction year t , not in a shopping district. $SD_i * S_{it}$ captures the heterogeneity in retail rents between retail properties which have been or will be in a shopping district but are, in a transaction year t , not in a shopping district and retail properties which are in a shopping district in transaction year t , without considering the tenant mix of shopping districts. $SD_i * S_{it} * MIX_{jt}$ allows the variation in tenant mix. It captures the heterogeneity in retail rents between retail properties which are, in transaction year t , located in shopping

districts with different tenant mix. We let the data decide whether the heterogeneity in retail rents depends on the tenant mix of shopping districts. Although we now estimate tenant mix in a parametric fashion, the results provide us with additional evidence of the association between retail rents and tenant mix by accounting for unobserved heterogeneity.

3.5 Results

3.5.1 Baseline results

Table 3.3 presents the results of our baseline models, i.e. Equation (3.2) and (3.3). Column (1) is the linear regression excluding the number of retail properties of each SBI sector classification within 100 meters of a rental transaction. We add the number of retail properties of each classification in Column (2).³⁷

As we can see, in Column (1), the coefficient of tenant mix is positive and significant, which implies a positive relationship between tenant mix and retail rents. In Column (2), where we control for competition of retail properties within 100 meters, the coefficient of tenant mix is still positive and significant but slightly lower. When the tenant mix of a shopping district increases by 1 unit, retail rents increase by 0.66% $(=(\exp(0.00658)-1)*100)$. Results from both specifications suggest that retail tenants pay higher rents in shopping districts with greater tenant mix.

The coefficients of control variables show expected signs. Using results of Column (2) for analysis, we see that the rent of a retail property located in a shopping mall will be about 6.65% higher than a retail property on the high street. Retail rents for newly built and renovated properties will be 16.53% and 16.18% higher respectively than an existing and unchanged property. The size of a shopping district also has a positive relationship with retail rents. It captures a part of the agglomeration effects of retail properties as we also control for the number of retail properties of each SBI sector classification within 100 meters. As for neighborhood characteristics, when the neighborhood's average income increases, retail rents will be higher, although this effect is not significant. There is, however, a negative and significant

³⁷The number of retail properties of each classification are calculated based on 3-digit SBI code.

Table 3.3: Baseline regression results

	(1)	(2)	(3)	(4)
	Linear	Linear	Semiparametric	Semiparametric
<i>MIX</i>	0.00880*** (0.00269)	0.00658** (0.00264)	See Figure 3.3	See Figure 3.3
Log of size	0.547*** (0.0141)	0.578*** (0.0135)	0.543*** (0.0127)	0.571*** (0.0120)
Chain (1=yes)	0.123 (0.0832)	0.112 (0.0791)	0.130 (0.0865)	0.118 (0.0815)
Log of size*Chain	0.0229 (0.0161)	0.0174 (0.0151)	0.0188 (0.0166)	0.0128 (0.0157)
Corner (1=yes)	0.0191 (0.0150)	0.00868 (0.0135)	0.0123 (0.0144)	0.00430 (0.0136)
Located in a shopping mall (1=yes)	0.0841*** (0.0210)	0.0644*** (0.0232)	0.0718*** (0.0207)	0.0616*** (0.0195)
Shopping district size (in 1,000 m^2)	0.000267** (0.000120)	0.000198* (0.000101)	0.000403*** (0.000102)	0.000267*** (9.65e-05)
Average income per resident (in 1,000 euros)	-0.00213 (0.00435)	0.000128 (0.00390)	0.00167 (0.00412)	0.00371 (0.00394)
Population density per km^2	-1.64e-05*** (4.48e-06)	-1.23e-05*** (4.44e-06)	-1.14e-05*** (4.36e-06)	-8.75e-06** (4.14e-06)
Log of distance to train station	0.0325 (0.0580)	0.00344 (0.0421)	0.0205 (0.0241)	-0.0113 (0.0231)
Log of distance to water body	0.0492*** (0.0172)	0.0331** (0.0132)	0.0605*** (0.0110)	0.0354*** (0.0105)
New (1=yes)	0.102** (0.0407)	0.153*** (0.0426)	0.0435 (0.0381)	0.0798** (0.0361)
Renovated (1=yes)	0.107*** (0.0400)	0.150*** (0.0442)	0.117** (0.0461)	0.159*** (0.0435)
SBI sector classification	no	yes	no	yes
Building periods	yes	yes	yes	yes
Transaction year fixed effects	yes	yes	yes	yes
Tenant category fixed effects	yes	yes	yes	yes
Urbanity fixed effects	yes	yes	yes	yes
PC4 fixed effects	yes	yes	yes	yes
Observations	6,864	6,864	6,863	6,863
Adjusted R^2	0.654	0.695	0.571	0.620

Note: Dependent variable is log of retail rent. Column (1) and (2) shows results of the linear hedonic model, while Column (3) and (4) show results from the semiparametric regression. SBI sector classifications in the table stand for the number of retail properties of each classification within 100 meters of a rental transaction. Estimates of the function of *MIX* from Column (3) and (4) are graphed in Figure 3.3. Clustered standard errors at PC4 level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

relationship between population density and retail rents. This is because population density measures the density of residents in the neighborhood. When population density is high, it means this neighborhood is mainly a residential area, not a highly

dense shopping district. Retail properties located in a residential area usually have lower rents. The other control variables also have expected coefficients, but they are not significant.

Columns (3) and (4) show results of the semiparametric regressions. If we compare them with Column (1) and (2), we can see the control variables have quite similar coefficients. The similar coefficients of control variables mean that the regression results of the semiparametric model are consistent. Contrary to linear regression, semiparametric regression does not estimate the coefficient of tenant mix. Instead, it outputs a smoothed graph of function $\Omega(MIX_{jt})$. Figure 3.3 illustrates the functional form of the log of rent (y-axis) and tenant mix (x-axis) based on the semiparametric regression results shown in Columns (3) and (4) of Table 3.3. The blue solid and red dashed curves represent the functional form based on Columns (3) and (4), respectively. In addition, we plot the histogram of tenant mix to show its distribution. It can be observed that the curves are steepest - where the marginal effects of tenant mix on retail rents are the highest (about 1.4%) - at the bulk of the distribution.

We can conclude from Figure 3.3 that, in general, tenant mix has a positive relationship with retail rents. Taking the red solid curve as an example, when tenant mix increases from 1 to 12, log of rent increases gradually from 10.44 to 10.49. For tenant mix between 12 and 30, log of rent soars from 10.49 to about 10.64 with a much steeper slope. For both intervals, we can observe an obvious positive relationship between tenant mix and retail rents. After tenant mix exceeds 30, the slope of the curve is almost flat.³⁸ This means that when tenant mix surpasses a certain level, an increase of tenant mix will not bring much increment in retail rents. It is apparent that the bulk of our observations have a tenant mix between 18 and 30. This means that, for the majority of our observations, retail rents have a clear and substantial positive relationship with tenant mix. When tenant mix is smaller than 20, the curve of Column (4) shows a higher return of log of rent with respect to tenant mix, compared to the curve of Column (3). When tenant mix is larger than 33, the curve of Column (3) shows a downward slope, which means now retail rents decrease with the increment of tenant mix. This is because when tenant mix is too high, compe-

³⁸These results are quite similar as our findings using categorized tenant mix, as shown in Column (2) of Table 3.7 in Appendix 3.C.

Figure 3.3: Functional form of tenant mix on retail rents based on semiparametric regression

Note: This figure shows estimates of the function $\Omega(MIX_{jt})$ with respect to tenant mix. The blue dashed curve represents the estimates from Column (3) of Table 3.3, while the red solid curve represents that of Column (4) of Table 3.3. Both curves together show a positive relationship between tenant mix and retail rents. This especially holds when tenant mix is smaller than 30. This graph also illustrates the nonlinearity of the relationship between tenant mix and retail rents.

tition between retail tenants dominates the market instead of positive externalities, which counteracts the positive effect of tenant mix. It can be seen that after including number of retail properties in each SBI sector classification in Column (4), this downward slope does not exist anymore.

The semiparametric regression confirms our conclusion from the linear regression that tenant mix has a positive relationship with retail rents in shopping districts. Furthermore, it does not specify a particular function form for retail rents and tenant mix, which allows us to describe their relationship in more detail and more accurately. When tenant mix is smaller than 30, we can observe an obvious and substantial positive relationship between tenant mix and retail rents. When tenant mix is higher than 30, this slope of the tenant mix becomes almost flat.

3.5.2 Results from the difference-in-difference model

Table 3.4 presents the results of Equation (3.4), the difference-in-difference model. As the aim of this model is to exploit the heterogeneity in retail rents between retail properties which have been or will be in a shopping district but are, in a transaction year t , not in a shopping district and retail properties which are in a shopping district in transaction year t . To facilitate this, we use all available rental transactions in the Netherlands, as opposed to the baseline model, which uses only rental transactions located in a shopping district when transacted. However, to control for potential endogeneity, for retail properties that have ever been or will be included in a shopping district, we use only those that are built before the shopping district is formed. As a result, a total of 7,963 rental transactions are used in the difference-in-difference analysis.³⁹

Column (1) of Table 3.4 shows the results of the difference-in-difference hedonic regression model. SD captures the heterogeneity in retail rents between retail properties that have ever been or will be included in a shopping district but, in transaction year t , are not in a shopping district and retail properties that are never included in a shopping district between 1996 and 2011. $SD_i * S_{it}$ captures the heterogeneity in retail rents between retail properties which are, in transaction year t , located in a shopping district and retail properties which have ever been or will be included in a shopping district between 1996 and 2011 but are, in transaction year t , not in a shopping district, without considering tenant mix. In Column (2) we add the interaction of $SD_i * S_{it}$ and MIX_{jt} , which captures the heterogeneity in retail rents between retail properties that are both in shopping districts, in transaction year t , but with different tenant mix. In Column (3) we add the number of retail properties within 100 meters of a rental transaction of each SBI sector classification.

In Column (1) we see that the rent of a retail property that has ever been or will be included in a shopping district but, in transaction year t , is not in a shopping district will be about 8.67% higher than a retail property that is never included in a shopping district between 1996 and 2011. The effect of being included in a shopping district when transacted is on average 16.77% if the heterogeneity in tenant mix of

³⁹Table 3.8 of Appendix 3.D presents descriptive statistics of observations used in the difference-in-difference analysis.

Table 3.4: Difference-in-difference regression results

	(1)	(2)	(3)
	Average Effect	Interacted with Tenant mix	Interacted with Tenant mix
<i>SD</i>	0.0831*** (0.0256)	0.0845*** (0.0256)	0.0829*** (0.0247)
<i>SD*S</i>	0.155*** (0.0295)	-0.00185 (0.0495)	-0.0218 (0.0421)
<i>SD*S*MIX</i>		0.00762*** (0.00207)	0.00336* (0.00185)
Log of size	0.594*** (0.0132)	0.596*** (0.0134)	0.621*** (0.0121)
Chain (1=yes)	0.357*** (0.0687)	0.343*** (0.0688)	0.257*** (0.0635)
Log of size*Chain	-0.0240** (0.0121)	-0.0217* (0.0121)	-0.0127 (0.0113)
Corner (1=yes)	0.0285* (0.0150)	0.0271* (0.0149)	0.00865 (0.0128)
Located in a shopping mall (1=yes)	0.0937*** (0.0199)	0.0971*** (0.0196)	0.0923*** (0.0195)
Average income per resident (in 1,000 euros)	0.00316 (0.00304)	0.00278 (0.00307)	0.00450 (0.00281)
Population density per km^2	-1.37e-05** (5.32e-06)	-1.40e-05*** (5.28e-06)	-8.66e-06** (4.14e-06)
Log of distance to train station	-0.0482 (0.0445)	-0.0526 (0.0448)	-0.0597* (0.0312)
Log of distance to water body	0.0449** (0.0176)	0.0436** (0.0174)	0.0262* (0.0142)
New (1=yes)	0.129*** (0.0355)	0.134*** (0.0353)	0.157*** (0.0358)
Renovated (1=yes)	0.130** (0.0561)	0.136** (0.0560)	0.184*** (0.0628)
SBI sector classification	no	no	yes
Building periods	yes	yes	yes
Transaction year fixed effects	yes	yes	yes
Tenant category fixed effects	yes	yes	yes
Urbanity fixed effects	yes	yes	yes
PC4 fixed effects	yes	yes	yes
Observations	7,963	7,963	7,963
Adjusted R^2	0.695	0.697	0.734

Note: Dependent variable is log of retail rent. This table shows the results of the difference-in-difference model. 7,963 observations are used in the regression, including those that have ever been or will be included in a shopping district and those that are never included in a shopping district. In Column (3), we add the number of retail properties within 100 meters of a rental transaction of each SBI sector classification. Clustered standard errors at PC4 level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the various shopping districts is disregarded. In Column (2), we add the interaction of $SD_i * S_{it}$ and MIX_{jt} . The results show that the heterogeneity in retail rents are largely explained by the variation in the tenant mix of shopping districts. This means that the heterogeneity in retail rents varies with the tenant mix of shopping districts. For example, the rent of a retail property in a shopping district, when transacted, with a tenant mix of 21 is about 0.89% higher than the rent of a retail property in a shopping district with a tenant mix of 20. Unsurprisingly, this varying heterogeneity becomes smaller in Column (3), as the number of retail properties of each SBI sector classification absorbs the competition effect from tenant mix (cf. Table 3.3). Using the results from Column (3), we can compute that the rent difference between retail properties in shopping districts with tenant mixes of 20 and 21 respectively is about 0.36%.

Based on these results, we observe a large heterogeneity in retail rents which depends on being included in a shopping district or not. In addition, the heterogeneity in retail rents depends, to a small degree at least, on the tenant mix of the shopping district.

3.6 Sensitivity analysis

To check the robustness of our results, we run a series of different sensitivity checks. First, we estimate models based on shopping districts delineated using different thresholds. Second, we use some other diversity indices to replace the tenant mix used in our baseline model to see if different choices of indices will have any influences on our results.

3.6.1 Different thresholds for shopping districts

We state above that one key element when delineating shopping districts is the choice of threshold. Different choices of thresholds result in different boundaries, shapes and sizes of shopping districts. It is evident that the tenant mix of a shopping district is sensitive to the delineation of the shopping district. We explore whether the choice of density threshold affects the relationship between retail rents and ten-

Table 3.5: Regression results with different thresholds

	(1)	(2)
	75th	85th
<i>MIX</i>	0.00491*	0.00404**
	(0.00278)	(0.00185)
Log of size	0.560***	0.567***
	(0.0152)	(0.0173)
Chain (1=yes)	0.0541	0.136
	(0.0897)	(0.107)
Log of size*Chain	0.0300*	0.0153
	(0.0173)	(0.0214)
Corner (1=yes)	0.0101	0.0188
	(0.0144)	(0.0170)
Located in a shopping mall (1=yes)	0.0479*	0.0147
	(0.0254)	(0.0290)
Shopping district size (in 1,000 m^2)	0.000485**	0.000892***
	(0.000189)	(0.000210)
Average income per resident (in 1,000 euros)	0.00109	0.00780
	(0.00441)	(0.00545)
Population density per km^2	-8.62e-06*	-4.56e-06
	(5.13e-06)	(4.38e-06)
Log of distance to train station	-0.0134	-0.0233
	(0.0453)	(0.0230)
Log of distance to water body	0.0480***	0.0170
	(0.0142)	(0.0163)
New (1=yes)	0.165***	0.0892
	(0.0585)	(0.0933)
Renovated (1=yes)	0.175***	0.135***
	(0.0433)	(0.0487)
SBI sector classification	yes	yes
Building periods	yes	yes
Transaction year fixed effects	yes	yes
Tenant category fixed effects	yes	yes
Urbanity fixed effects	yes	yes
PC4 fixed effects	yes	no
City fixed effects	no	yes
Observations	5,600	3,746
Adjusted R^2	0.688	0.664

Note: Dependent variable is log of rent price. This table show results for shopping districts delineated based on different thresholds. Since the threshold is higher than the one used in the baseline model, shopping districts used in this table are fewer and smaller in size. As a result, fewer observations are used in both columns. Clustered standard errors at PC4 level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

ant mix.

We reconstruct two sets of shopping districts by choosing the thresholds of den-

sity to be the 75th and 85th percentiles of the retail property density.⁴⁰ As the thresholds become higher, the constructed shopping districts shrink compared with shopping districts that we use in our baseline regression. As a consequence, the number of rental transactions that fall into a shopping district declines.

Table 3.5 reports the regression results using shopping districts constructed based on the 75th and 85th percentile in Columns (1) and (2), respectively. The number of observations - retail properties in shopping districts - are 5,600 and 3,746, respectively.⁴¹ Results in both columns show positive coefficients, which confirms the positive relationship between retail rents and tenant mix. This implies that the conclusion based on our main results remains the same. However, compared with our baseline results, the effect of tenant mix on retail rents becomes smaller. When *MIX* increases by 1 unit, retail rents increase by 0.49% and 0.40% in columns (1) and (2), respectively.

3.6.2 Alternative tenant mix indices

In our baseline models, we calculate the tenant mix by using the formulation of the Herfindahl Index and the number of retail properties in each SBI sector classification. It is reasonable to argue that the positive effect of tenant mix is the result of choosing this particular type of diversity index. Therefore, we check its robustness by using two other well-known diversity indices.

According to Equation (3.1), the Herfindahl Index gives weight to SBI sector classifications that account for a large proportion in a shopping district. It is sensitive to the concentration level of shopping districts. To compensate for this effect, we compute an alternative tenant mix index by using the Shannon Index, which is another commonly used index for measuring diversity. The Shannon Index is defined

⁴⁰More explicitly, the involved density thresholds are respectively 6,148 jobs per km^2 and 10,201 jobs per km^2 .

⁴¹Another consequence is, when we use the 85th percentile to construct shopping districts, many shopping districts we get are as small as (if not smaller than) a PC4 area. This makes us to use city fixed effects instead of PC4 fixed effects in Column (2). Because if we continue to use PC4 to control for location fixed effects, the effect of tenant mix will be absorbed by the fixed effects such that the coefficient of tenant mix becomes small and insignificant.

Table 3.6: Regression results with different diversity indices

	(1)	(2)
	Shannon	Weighted Herfindahl Index
<i>MIX</i>	0.0846** (0.0331)	0.00619* (0.00338)
Log of size	0.579*** (0.0134)	0.578*** (0.0135)
Chain (1=yes)	0.116 (0.0797)	0.114 (0.0790)
Log of size*Chain	0.0167 (0.0152)	0.0170 (0.0150)
Corner (1=yes)	0.0167 (0.0152)	0.00927 (0.0135)
Located in a shopping mall (1=yes)	0.0643*** (0.0234)	0.0641*** (0.0234)
Shopping district size (in 1,000 m^2)	0.000163* (9.63e-05)	0.000213** (0.000106)
Average income per resident (in 1,000 euros)	0.000396 (0.00394)	0.000584 (0.00394)
Population density per km^2	-1.22e-05*** (4.45e-06)	-1.18e-05*** (4.43e-06)
Log of distance to train station	0.00391 (0.0417)	0.00482 (0.0422)
Log of distance to water	0.0335** (0.0131)	0.0337** (0.0131)
New (1=yes)	0.154*** (0.0426)	0.155*** (0.0429)
Renovated (1=yes)	0.151*** (0.0445)	0.151*** (0.0452)
SBI sector classification	yes	yes
Building periods	yes	yes
Transaction year fixed effects	yes	yes
Tenant category fixed effects	yes	yes
Urbanity fixed effects	yes	yes
PC4 fixed effects	yes	yes
Observations	6,864	6,864
Adjusted R^2	0.696	0.695

Note: Dependent variable is log of retail rent. This table presents results using alternative indices to measure tenant mix. The first column shows results using Shannon Index, while the second column shows results with weighted Herfindahl Index. Clustered standard errors at PC4 level in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

as follows:

$$\text{Shannon Index}_{jt} = - \sum_{l=1}^m P_{ljt} \ln P_{ljt},$$

where P_{ljt} is the proportion of SBI sector classification l compared to all retail properties within a shopping district j in year t . Shannon Index is very similar to Herfindahl Index but it gives lower weight to SBI sector classifications that account for a large proportion. Shannon Index must be larger than zero, and it increases when a shopping district gets more diverse.

The second alternative tenant mix index we propose is the adjusted, or weighted, Herfindahl Index. Compared with the standard Herfindahl Index we used previously, the weighted Herfindahl Index uses number of jobs as weight for each retail property. Retail properties of different scales play different roles in determining the tenant mix, as well as the attractiveness of a shopping district. To reflect this, we extend the influence of some retail properties, anchor stores for example, on the tenant mix of the shopping district by using number of jobs as weight. Similar as Equation (3.1), we take the *reciprocal* of the weighted Herfindahl Index.

Table 3.6 presents the regression results using alternative indices. Column (1) depicts results using Shannon Index, while Column (2) uses (the *reciprocal* of) weighted Herfindahl Index. Both coefficients of tenants mix – alternatively defined – are positive and significant. When Shannon Index of a shopping district increases by 1 unit, retail rents increase by about 8.83%. Similarly, retail rents are about 0.62% higher with 1 unit increment of weighted Herfindahl Index. Both indicates a positive relationship between retail rents and tenant mix. This shows that our results are consistent with the choices of diversity indices.⁴²

3.7 Conclusion

This paper investigates the relationship between retail rents and tenant mix for high street shopping districts in which ownership is fragmented and tenant mix is outside the control of individual property investors. Data on high street shopping districts

⁴²Note that these indices have different scales. Therefore, it would be illogical to compare the coefficients in two columns directly.

in the Netherlands between 1996 and 2011 reveal that retail rents are significantly related to tenant mix. Shopping districts with greater tenant mix show higher retail rents relative to districts with lower tenant mix. In general, we conclude that there is a positive relationship between tenant mix and retail rents.

Our analysis is based on shopping districts for which boundaries are typically difficult to measure. We argue that our strategy enables the precise delineation of shopping district boundaries. While typical approaches based on all-parcel files provide information on intended land use, it also potentially mismeasures the boundaries of the actual functional economic shopping district. Instead, we propose to use kernel density techniques based on granular retail property information to precisely indicate the economic functioning shopping districts. For each of these shopping districts we calculate tenant mix based on SBI sector classification. These sector classifications are commonly used and provide an efficient way of characterizing retail activity. We use the *reciprocal* of Herfindahl index to determine the tenant mix. We then combine our measures of tenant mix with retail transaction data. Our empirical strategy is based on a set of different regression models. First, we estimate a set of linear regression models for rent transactions currently located in a shopping district. Second, we explore the potential nonlinear relationship between retail rents and tenant mix by estimating a semiparametric model. Third, we exploit the unobserved heterogeneity in retail rents and the variation in the tenant mix of shopping districts by estimating a difference-in-difference model. The main results of tenant mix turn out to be unaffected in the sensitivity analyses. We explore differences across various thresholds and tenant mix indices. Neither of these results jeopardize our main findings.

While our research addresses many of the challenges in estimating tenant mix effects on rents, a number of new directions for future research can be indicated. First, the question arises if heterogeneity in tenants across shopping districts drive these results. Second, tenant mix may in actual fact relate to differences in convenience goods, shopping good, and specialty goods. Third, although we have tried to control for competition between retail tenants, this is not the focus of this paper. The trade-off between agglomeration and competition and its influence on tenant mix needs further exploration. These, amongst other issues, remain for future research.

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Appendix 3.A Theoretical model

3.A.1 Matching function

Following the matching framework of Moen (1997), we suppose $M(u, v)$ is the matching function representing the matches of retail property investors and retail tenants, where u is the rate of retail tenants searching for a property (relative to the total number of retail tenants) and v is the vacancy rate of retail properties on the market.⁴³ Following standard assumptions, we let $M(u, v)$ be an increasing concave function, homogeneous of order one in (u, v) , so that we have

$$g(\theta) = \frac{M(u, v)}{v} = M\left(\frac{u}{v}, 1\right) = M(\theta, 1),$$

and

$$h(\theta) = \frac{M(u, v)}{u} = M\left(1, \frac{v}{u}\right) = M\left(1, \frac{1}{\theta}\right),$$

where $g(\theta)$ is the transition rate of a vacant property becoming occupied, and $h(\theta)$ is the arrival rate of retail tenants finding a vacant property.⁴⁴ θ is equivalent to u/v which measures the tightness of the market. During recessions of the market, the number of retail tenants who search for vacant properties (u) decreases and the number of vacant properties (v) increases, which leads θ and $g(\theta)$ to decrease.⁴⁵ The opposite happens during booming periods of the market.

After having been matched, the retail tenant considers consumers' demand as well as tenant mix in the shopping district and starts to conduct one type of retail activity immediately. Meanwhile, there are also some occupied retail properties that break down and decide to end their rental contract. As a result, these retail properties enter the market to join the matching process again. We suppose this happens at a constant rate δ , which is determined exogenously. Therefore, occupied properties

⁴³The matching function $M(u, v)$ captures the frictions of the market. The frictions come from search costs and time delays during the search process.

⁴⁴Clearly, we can see that $g(\theta) = \theta h(\theta)$.

⁴⁵ $g(\theta)$ is positively related to θ because when there are more searching retail tenants relative to vacant properties, vacant properties can be rented out more easily. On the contrary, $h(\theta)$ is negatively related to θ . When there are more searching retail tenants relative to vacant properties, it is more difficult for a retail tenant to find a vacant property.

become vacant at rate $\delta(1 - v)$. In steady state, the matching rate and breaking down rate are equivalent, so that

$$M(u, v) = \delta(1 - v).$$

Since $M(u, v)$ can be written as $g(\theta)v$, we get

$$g(\theta)v = \delta(1 - v).$$

Rewrite this and we get

$$v = \frac{\delta}{g(\theta) + \delta}. \quad (3.5)$$

Equation (3.5) is the steady state vacancy rate, which is determined by the transition rate $g(\theta)$ and breaking down rate δ .

3.A.2 Retail property investors

Retail property investors own retail properties. When a retail property is occupied, investors obtain rental income from the retail tenant who rents this property. If the retail property is vacant, investors have to search for a retail tenant at a cost. This cost consists of two parts, search cost and management cost for holding a vacant property.

Let I_v denote the expected discounted profits of investors with vacant properties and I_o denote the expected discounted profits of investors that own occupied properties. The present value of I_v is represented as follows:

$$\sigma I_v = -c + g(\theta)(I_o - I_v), \quad (3.6)$$

where σ is the discount rate and c is the cost for investors with vacant properties. $g(\theta)(I_o - I_v)$ represents the expected gain from renting out a property. The expected profit of holding a vacant property equals the expected gain from matching minus the cost of holding a vacant property. Similarly, the expected discounted profits of

investors with occupied properties, I_o , can be written as:

$$\sigma I_o = r - \delta (I_o - I_v), \quad (3.7)$$

where r is the rent of an occupied property. $\delta(I_o - I_v)$ measures the loss if an occupied property becomes vacant. The expected discounted profit of an investor with an occupied property equals the rent of this property minus the expected loss if this property becomes vacant. Based on Equation (3.6) and (3.7), we can get

$$\sigma I_v = \frac{g(\theta) r - c(\sigma + \delta)}{\sigma + \delta + g(\theta)}. \quad (3.8)$$

Rearranging this yields

$$g(\theta) = (\sigma + \delta) \frac{\sigma I_v + c}{r - \sigma I_v}. \quad (3.9)$$

From Equation (3.9), we can see that $g(\theta)$ is negatively related to r . This indicates a negative relationship between the prosperity measure of the market, θ , and retail rents, r . When θ is small, it means the market is in a depression period with a lot of vacant retail properties and thus retail rents will be relatively low.

3.A.3 Retail tenants

Once retail tenants find a vacant retail property, they will start their retail activity immediately. However, the choice of the type of retail activity depends on consumers' needs and tenant mix of the shopping district. Because of the existence of shopping externalities, a retail tenants must take other retail tenants in the proximity into account when deciding on their business type. We suppose $f(m; X)$ to be the production function of a retail tenant, where m is the shopping district's tenant mix and X represents all other input factors of the production function.⁴⁶ We assume the first-order derivative of $f(m)$ exists. Retail tenants can only start their retail activity after finding a retail property. The expected profit of a retail tenant who has not found

⁴⁶We assume tenant mix m of a retail tenant is exogenous, which means m is independent of all other input factors, X . Both m and X are non-negative. Since our focus is on tenant mix, in the following context we write the production function as $f(m)$. This does not affect conclusion.

a property is equivalent to its expected capital gain from property search minus its search costs. If the expected discounted profit of a retail tenant who has not found a property is P_v , then we get

$$\sigma P_v = -z + h(\theta)(P_o - P_v), \quad (3.10)$$

where z is the search cost of tenants and P_o is the expected discounted profit of a retail tenant who has a shop. $h(\theta)(P_o - P_v)$ is the expected capital gain from searching. Similarly, we can get the equation of P_o as

$$\sigma P_o = f(m) - r - \delta(P_o - P_v). \quad (3.11)$$

$f(m) - r$ is the net return of a retail tenant conducting retail activity. Its expected discounted profit equals its net return minus the expected loss of breaking down.

Since the market is competitive and retail tenants can enter the market freely, in equilibrium the expected profit of a retail tenant who is searching for a property must be equivalent to zero, which means $P_v = 0$. Substituting this into Equations (3.10) and (3.11), we can get

$$P_o = \frac{z}{h(\theta)} = \frac{f(m) - r}{\sigma + \delta}. \quad (3.12)$$

3.A.4 Equilibrium

We assume that rents are determined by Nash bargaining. The solution to Nash bargaining, r^* should maximize the product of investors' and tenants' profits from the matching process weighted by their bargaining power. Let β represent the bargaining power of retail tenants, and $(1 - \beta)$ be the bargaining power of retail property investors, where $0 < \beta < 1$. According to Nash bargaining, there exists a rent level r^* which solves the problem

$$\max_r (I_o - I_v)^{1-\beta} (P_o - P_v)^\beta. \quad (3.13)$$

Taking the first derivative, we get

$$(1 - \beta)(P_o - P_v) = \beta(I_o - I_v). \quad (3.14)$$

Note that in equilibrium $P_v = 0$. Combine this equation with Equation (3.5), (3.8) and (3.12), we are able to calculate the equilibrium rent r^* :

$$r^* = \frac{(1 - \beta)(\sigma + \delta + g(\theta))f(m) - \beta c(\sigma + \delta)}{\sigma + \delta + (1 - \beta)g(\theta)}. \quad (3.15)$$

This indicates that the equilibrium rent r^* is related to tenant mix.

Take the first derivative of r^* over tenant mix m , and we get

$$\frac{dr^*}{dm} = A \frac{df(m)}{dm}, \quad (3.16)$$

where $A = \frac{(1-\beta)(\sigma+\delta+g(\theta))}{\sigma+\delta+(1-\beta)g(\theta)}$. Note that $A > 0$, so that the signal of Equation (3.16) depends on the signal of $\frac{df(m)}{dm}$, which measures the relationship between the retail tenant's production function and tenant mix. This indicates that retail rent is indeed affected by the tenant mix of the shopping district, but the overall effect remains indecisive. It is the aim of our empirical analysis to answer the question with regard to the relationship between retail rents and tenant mix.

Appendix 3.B Data appendix

3.B.1 Retail properties

The granular data of registered retail properties come from the Dutch Chambers of Commerce. These datasets are collected annually from 1996 to 2011 and include all retail properties registered at the Dutch Chambers of Commerce in the corresponding year. For each retail property, we know its precise location, SBI sector classification, and number of jobs. Figure 3.2 illustrates the locations of all registered retail properties in 2011.

3.B.2 Shopping districts

Shopping districts are constructed based on the spatial distribution of retail properties. We use GIS techniques to delineate shopping districts. The procedure consists of the following steps. First, we create grids of 10 by 10 meters for all of the Netherlands. Next, for each grid we calculate the density of retail properties within 100 meters of the grid by using the method of kernel density. When calculating the density, we take the number of jobs at each retail property as the weight for each property. The choice of using number of jobs as the weight of each retail property has practical reasons. We experimented both with the weights and without the weights. When no weights are used, grids located at the edge of a shopping district usually have a low-density value, so that constructed shopping districts are smaller than their actual size. This has serious consequences in the later stage of our empirical analysis, because retail properties at the edge of a shopping district are often excluded from the corresponding shopping district. Conversely, this problem may be relieved when the weights are used. Then, we use a predetermined threshold of density and, for adjacent grids with density exceeding this threshold, we merge them to create a shopping district. We set this threshold of density to be 3,421 jobs per km^2 , which is equivalent to the 65th percentile of the retail property density distribution in 2010. We apply the same procedures to construct shopping districts for every year between 1996 and 2011. In this way, we are able to capture the development of shopping districts over time. Figure 3.4 shows all shopping districts constructed in

Figure 3.4: Shopping districts of the Netherlands, 2011

the Netherlands in 2011. Figure 3.5 shows the development of shopping districts in the city of Groningen from 1996 to 2011. The left panel shows the shopping districts in Groningen in 1996, while the right panel shows the shopping districts in 2011. Comparing these two maps, one observes changes in shopping districts over time.

3.B.3 Rental transactions

Our data on retail rents come from Strabo. The data include 9,436 rental transactions for the Dutch retail markets from 1996 to 2011. All these observations refer to new rental contracts, which means extensions of existing rental contracts are not included in the data. The data include information on annual rent, property size, precise

Figure 3.5: Shopping districts of Groningen, 1996 and 2011

location, name of the tenant and year of transaction. Retail rents are nominal market rents.⁴⁷ We geocode all rental transactions and subsequently map these to the all-parcel file of the Netherlands (BAG data). Finally, we map our rental transaction data onto the shopping districts in the year the property was transacted. Figure 3.6 shows the locations of all these rental transactions.

Out of these observations, we have 6,864 rental transactions which are in a shopping district when transacted. These rental transactions are used in the hedonic model analysis. Figure 3.7 compares the trends in average annual rent (per m^2) for rental transactions located in a shopping district when transacted and those not. It can be seen that the trends in both panels of Figure 3.7 follow similar pattern. Especially the average annual rent per m^2 of properties located in a shopping district when transacted is almost twice that of properties that are not in a shopping district when transacted.

Because of the limited number and distribution of our rental transactions, only

⁴⁷In the Netherlands, rents typically relate to nominal fixed rents with annual rent increases (at least till 2013). Furthermore, rents relate to market rents so that no information on rent incentive is known.

Figure 3.6: Location of all rental transactions from 1996 to 2011

some of the shopping districts incorporate rental transactions. However, it is important to know the percentage of our occupied shopping district (i.e. shopping districts with at least one rental transaction in it) out of all shopping districts in the Netherlands in each year. To do so, we calculate the size of all shopping districts and the size of occupied shopping districts for each year. The result is presented in Figure 3.8. We can see that the overall size of shopping districts in the Netherlands increases gradually from 1996 to 2011. However, the size of occupied shopping districts in each year fluctuates around 20,000,000 square meters. The grey line in the graph shows the percentage of the size of occupied shopping districts out of the size of all shopping districts. It is apparent that this line fluctuates around 30%.

Figure 3.7: The development of average annual rents

Figure 3.8: Shopping districts with at least one rental transaction observed versus all shopping districts

from 1996 to 2011

Appendix 3.C Different specifications of the hedonic price model

Table 3.7: Different specifications of the hedonic price model

	(1)	(2)
	Quadratic form	Categorized tenant mix
<i>MIX</i>	0.0229*** (0.00815)	
<i>MIX</i> ²	-0.000431** (0.000180)	
Categorized <i>MIX</i> (reference: <i>MIX</i> < 12)		
Dummy (12 ≤ <i>MIX</i> < 25)		0.125*** (0.0470)
Dummy (25 ≤ <i>MIX</i> < 35)		0.115** (0.0499)
Dummy (<i>MIX</i> ≥ 35)		0.0854 (0.0630)
SBI sector classification	yes	yes
Building characteristics	yes	yes
Building periods	yes	yes
Transaction year fixed effects	yes	yes
Tenant category fixed effects	yes	yes
Urbanity fixed effects	yes	yes
PC4 fixed effects	yes	yes
Observations	6,864	6,864
Adjusted <i>R</i> ²	0.696	0.695

Note: Dependent variable is log of retail rent. This table represents results based on other specifications of the hedonic price model. The first column include results using the quadratic *MIX*. The second column shows results using categorized tenant mix. Both results show possibility of a nonlinear relationship between tenant mix and retail rents. Clustered standard errors at PC4 level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 3.D Descriptive statistics of rental transactions used in difference-in-difference analysis

Table 3.8: Descriptive statistics of rental transactions used in difference-in-difference analysis

	Mean	Std. Dev.	Median	Min	Max
Rent price	50,429.140	43,390.420	36,302	9,000	338,380
Rent price per m^2	242.345	188.783	189	16	2,351
<i>MIX</i>	15.927	11.041	19.674	1	40.806
Property size (m^2)	324.686	447.309	180	20	8,390
Transaction year	2003.581	4.493	2004	1996	2011
Average income per resident (in 1,000 euros)	15.203	6.018	13.75	0	45.5
Population density per km^2	5,815.817	3,755.953	5,337	2.00	28,060
Distance to train station (m)	1,998.303	3,129.482	893.559	27.268	22,766.360
Distance to water (m)	222.054	171.956	181.425	2.265	1,180.464
Chain store (1=yes)	0.367	0.482			
Corner store (1=yes)	0.145	0.353			
Located in a shopping mall (1=yes)	0.209	0.407			
<i>SD</i>	0.828	0.378			
<i>S</i>	0.702	0.458			
Building status					
Existing (1=yes)	0.906				
New (1=yes)	0.075				
Renovated (1=yes)	0.019				
Building periods					
<1945	0.423				
1945-1960	0.122				
1961-1970	0.065				
1971-1980	0.077				
1981-1990	0.062				
1991-2000	0.113				
>2000	0.138				
Number of rental transactions	7,963				

Note: This table presents statistics of observations used in the difference-in-difference analysis. In our baseline regression, we use only rental transactions that are located in a shopping district when transacted. However, based on our difference-in-difference setting, here we include all rental transactions but, for retail properties that has ever been or will be included in a shopping district, we exclude those ones built after the shopping district is formed.

Chapter 4

Economic Depreciation of Commercial Real Estate Properties across Europe

Abstract

This paper investigates regional variations in depreciation rates of commercial real estate properties across Europe. We deduce net depreciation rates based on a comparison of selling prices for properties of different ages and associate these to the regional economy. We use a large sample of commercial real estate sales across Europe from 2003 to 2017. We found significant regional variations in depreciation rates and also that these vary across market segments. We examine regional variations in depreciation rates by probing more deeply into regional economic drivers including disposable income, real GDP, and unemployment rate. We find that real estate markets with lower depreciation rates are also those with higher levels or increments in the value of economic drivers.

Keywords: *depreciation, commercial real estate, hedonic price, regional economy*

4.1 Introduction

Whether and by how much real estate assets depreciate, *i.e.* the reduction in value of a stock of real assets, is a fundamental concern to real estate investors.⁴⁸ Real estate investors hold managed real assets for income-generating purposes, as part of which they buy, lease-out, maintain, and sell off property. Uncertainties concerning economic depreciation, exit yields, and sale prices constitute a real risk to investors' returns.⁴⁹ Economic depreciation rates can be substantial and rough estimates vary anywhere up to 5% per year, such that, for a typical holding period of seven to ten years, total depreciation may amount to roughly 40% of original investment, although substantial variations exist in depreciation rates across segments and regions. Investors, in due diligence studies, therefore seek to forecast future cash flows and depreciation rates at the time of buying real estate assets. Also, since economic depreciation rates vary across regional markets, investors take this into account when considering in what regions to invest.

By precisely how much real estate assets depreciate and what drives variations across market segments and regional markets is an ongoing topic in the literature. To obtain an accurate depreciation rate for a given property at a particular location, one would need precise information on the historical building cost of the property and the capital expenditures over its lifetime T . Depreciation estimates are less precise when one can only observe properties that are actually bought and sold at specific time intervals between period 0 and period T . Moreover, the observed sales price not only includes the value of the building structure but also the value of the land (for more detailed information, see Diewert & Fox, 2016). Much of the recent literature determines economic depreciation based on an age–price relationship in a hedonic framework (Wilhelmsson, 2008; Diewert et al., 2015; Bokhari & Geltner, 2018; Francke & Van de Minne, 2017; Diewert & Shimizu, 2017; Bokhari & Geltner, 2019; Yoshida, 2020).⁵⁰ We build on these contributions, and explore the variations in net

⁴⁸Here, depreciation refers to economic depreciation in order to clearly differentiate it from corporate finance tax-related definitions of depreciation.

⁴⁹Exit yields typically exceed initial yields; or equivalently, assets are sold at lower prices, *ceteris paribus*.

⁵⁰Longitudinal comparisons consider the same property at various selling dates and possibly different stages of the business cycle. Cross-sectional comparisons compare different properties at similar sales dates and identical stages of the business cycle.

depreciation rates across regions and the interplay with economic drivers.

Net depreciation, based on a comparison of sales prices with varying building age, may be a consequence of several aspects. (1) *Physical deterioration*, or the decline in asset value due to the decay of a property because of weather and use over time. Physical deterioration includes the deterioration of the inner structure of the building, the outer facade of the building, and installations such as lifts, water, and air conditioning services. (2) *Functional deterioration*, or the decline in asset value due to the obsolescence of the interior structure and design of a property as a result of new innovations and technologies. Examples are 16th century warehouses which became functionally obsolete after the introduction of mass production, or energy-inefficient buildings in an era moving towards a sustainable society. (3) *Economic conditions*, or the change in asset value due to a reduced willingness to pay for properties of increasing age because investors perceive increased risk of maintenance costs or vacancies. Diewert & Fox (2016) argue that depreciation in commercial properties is primarily driven by economic conditions rather than deterioration. Consequentially, determining depreciation, or identifying a coefficient for age, is a classical problem due to the mixture of alternative explanations including properties of varying qualities at the time of construction, different wear and tear patterns, varying levels of maintenance over time, and varying market conditions at the times of sale.

The goals of our paper are twofold. First, we aim to determine the age–asset price relationship of commercial real estate properties. We will argue that our method provides an estimate for relative net depreciation rates across regional markets in Europe. We use the RCA-Europe commercial real estate property sales database for the period between 2003 and 2017, divide the data into three market segments (office, retail, and industrial), and then estimate net depreciation rates for each segment. The data contain information on sales price, sales date, and a rather detailed set of property characteristics. Our paper contributes to the growing literature on depreciation in real estate. Most of the literature on depreciation focuses on residential properties (see, e.g., Smith, 2004; Francke & Van de Minne, 2017). Smith (2004) shows that the depreciation estimate depends on the relationship imposed between age and price. Further, the measured depreciation also depends on the specific property, including the specific location and the timing of a sale, suggesting that longitudinal micro-

data are an appropriate basis (Francke & Van de Minne, 2017). Few studies estimate the depreciation of commercial real estate properties, and even fewer consider variations in depreciation rates among industrial, office, and retail properties.⁵¹ One of the exceptions is the work by Bokhari & Geltner (2018) and their accompanying paper (Bokhari & Geltner, 2019) in which they estimate depreciation rates for commercial real estate property. They use a longitudinal micro-database covering over 100,000 commercial property sales across MSAs in the US between 2001 and 2014. They calculate an average annual depreciation rate of 1.5% although they find substantial variations across segments and MSAs. Another notable effort is by Levkovich et al. (2018) who use transactions in the Netherlands to estimate the depreciation of commercial real estate properties in different market segments and construction cohorts. They conclude that the depreciation of commercial real estate is heterogeneous over market segments and construction cohorts. We will complement this existing literature by analyzing the heterogeneity in net depreciation, or the age–asset price relationship, for market segments across European commercial real estate markets.

Second, we aim to explore further the regional variations in net depreciation rates across Europe using data on regional economic drivers. We will link depreciation to economic drivers on the basis that asset values have been related to aggregate economic conditions (cf. Plazzi et al., 2008). Again, there is only limit literature that examines the age–asset price relationship in conjunction with aggregated economic drivers. The substantive question we aim to answer is what specific drivers of the regional economy vary with estimated depreciation rates. In examining this relationship, we relate to the literature on depreciation in housing markets. Rosenthal (2014) indicates that depreciation in housing stock is lower in times of price inflation, suggesting that these depreciation rates are related to economic conditions. Others (like, Smith, 2004; Harding et al., 2007; Wilhelmsson, 2008; Bokhari & Geltner, 2018) also point towards variations in economic conditions across local markets but do not explicitly address the interplay with depreciation rates. One study that comes somewhat closer to our approach is by Yoshida (2020) who links depreciation rates to

⁵¹Most studies on depreciation in the commercial real estate sector use appraisal-based depreciation rates (see, e.g., Crosby et al., 2016). They tend to find a mean depreciation rate for offices and industrial real estate of around 0.1%. The disadvantage of appraisal-based data is that it risks missing asset price fluctuations because of smoothing and lagging (Darrat & Glascock, 1993).

local variables including a property's height, road frontage, distance to the nearest railway station, and site shape. However, this study does not consider macroeconomic variables. We therefore take up the challenge of investigating the interplay of building depreciation rates with regional economic drivers more explicitly. We conjecture that, with the data we have access to, variations across regional markets can be detected. We examine over 8,000 commercial real estate property sales across 701 NUTS 3 regions and 16 countries in Europe. The data we use relate to typical investment properties and most of them are within the European Union where local markets vary in terms of the regional context.⁵²

The remainder of our paper is as follows. Section 4.2 provides a synthesis of the literature on depreciation. Section 4.3 presents the empirical model used in our analysis. Section 4.4 introduces our research data and Section 4.5 reports our baseline results. To conclude, Section 4.6 discusses the findings and draws conclusions.

4.2 Recent literature

The recent literature on property depreciation rates has investigated the age–asset price relationship. Most of the discourse is on whether this age–asset price relationship truly identifies the average depreciation rate of building structures as many studies ignore land values, capital expenditures, and potential demolition costs.⁵³ It is fundamental to our understanding that depreciation is not observed but rather deduced based on a comparison of sales prices, $P_t - P_{t-k}$, at different moments in time, t and k , or $\Delta P_t / \Delta t$.

Asset prices reflect prevailing market conditions in terms of rental cash flows, discount rates, and investment capital availability. For instance, asset price spirals – referring to an upswing in asset prices during periods of yield compression, and a subsequent asset price decline afterwards – complicate depreciation rates estimates.⁵⁴ As a consequence, the depreciation rate of a certain property at a specific

⁵²Most countries we examine have civil rights, the exception being the UK. The origins of the legal system impact on property rights, which affect real estate markets (Porta et al., 2008).

⁵³For a more detailed discussion, see Bokhari & Geltner (2018); Diewert & Fox (2016); Francke & Van de Minne (2017); Diewert & Shimizu (2017); Yoshida (2020).

⁵⁴Fiscal depreciation rates refer to a gradual decrease in an asset's value over its useful life irrespective of variations in market price.

moment in time might be higher in a cold market than later when the market turns hot, even though the property is then older. Observed fluctuations in depreciation over time thereby link to asset pricing in which variations in future rents and future discount rates play a role (Plazzi et al., 2010).

Real estate properties are embedded in regional economies and real estate asset prices vary across space. A regional economy encompasses a broad set of overlapping and mutually dependent drivers that link productivity and regional economic activity, population, and local land-use restrictions and the supply of developable land. Plazzi et al. (2010) refer to these as the geographic, demographic, and local economic conditions of real estate asset markets. Lieser & Groh (2013) highlight additional drivers including sector structure and the share of business services in the economy, access to capital markets and banking services, and the legal and institutional framework. All these drivers shape the regional market context in which real estate cash flows are generated and asset prices are set. As such, cross-sectional differences in asset prices can be linked to cross-sectional differences in regional economies. Related to this, local clustering and agglomeration add to the observed cross-sectional variation (Van der Vlist et al., 2019).

In addition to cross-sectional variations across space, real estate cash flows, discount rates, and asset prices respond differently as economic conditions change over time. Regional land-use regulations and the supply of developable land play an important role in adjustments to the stock over time through new constructions and the redevelopment of existing stock. Markets with rather inelastic supplies show lower depreciation rates than markets with a rather elastic supply (Brouwer, 2014).

Pulling the recent body of literature together, we see that the age–asset price relationship captures time variation in cross-sectional asset price differences of properties across regional markets. The extracted depreciation rate summarizes differences across properties of varying qualities at the time of construction, differing wear and tear patterns, varying levels of maintenance, and differing market conditions in terms of rental cash flows and discount rates at the time of sales. For these reasons, depreciation rates are one of the most complex parameters to determine (Diewert & Shimizu, 2017).

In terms of the empirical methodology adopted, the age–asset price relationship

is generally examined in a standard linear model framework (see, e.g. Smith, 2004; Harding et al., 2007; Wilhelmsson, 2008; Bokhari & Geltner, 2018; Francke & Van de Minne, 2017). In this framework, sales price is a function of age and a set of property control variables including location and time. The discourse in the empirical literature on depreciation can be summarized along three dimensions.

First, the functional form of the age–asset price relationship. One of the earliest contributions is by Hulten & Wykoff (1981). In their framework, a Box-Cox transformation is used to model the age–asset price relationship. The Box-Cox transformation is a highly flexible functional form in which the data governs the functional form of the age–price relationship and they found that real estate depreciation rates follow a geometric form with age. Other authors have used a polynomial form based on age or a piece-wise linear structure (for a discussion, see Diewert & Shimizu, 2017). Goodman & Thibodeau (1995) show both theoretically and empirically that depreciation is non-linear and that newer properties depreciate at a higher rate than older properties. More recent contributions use property life expectancy tables to incorporate property survival rates in the equation (Diewert & Shimizu, 2017; Bokhari & Geltner, 2019). While including property survival rates corrects for possible selection bias, the conditional probabilities of actually demolishing turn out to be very small. Diewert & Shimizu (2017) find, for Japan, that demolishing rates climb rather rapidly after the age of 67. Bokhari & Geltner (2019) find lower conditional probabilities of demolition for the US, and consequently higher survival rates.⁵⁵

Second, the discourse addresses the operationalization of asset value as a dependent variable. Early contributions used the value of rents and capital expenditures to infer the appraised asset price. Appraisal-based data however run the risk of mis-stating asset price fluctuations because of smoothing and lagging (Darrat & Glascock, 1993). Compared to appraisal-based data, sales prices come with the great advantage of including actual price fluctuations. Although sales prices seem preferable, some criticize the use of sales prices because these include the value of land. Bokhari & Geltner (2018) argue that using sales prices underestimates depreciation rates as building structures depreciate but land tends not to. Francke & Van de

⁵⁵While there are no data on survival rates for Europe, we suspect survival rates in Europe are even higher.

Minne (2017) proposed a model, for housing, to disentangle the value of the property and the value of land. While sound, adjusting for the value of land is only particularly important if it constitutes a substantial proportion of the asset value. Therefore, in order to prevent any bias related to the absence of information on land values, we will present estimates of relative depreciation rates when characterizing regional variations.

Third, a recurrent theme is how to capture the spatial variation in the age–asset price relationship. Malpezzi et al. (1987) estimate depreciation rates for housing by metropolitan area and find that depreciation rates vary across metropolitan areas. They found depreciation estimates anywhere between 0.5 and 2% per year. They indicate that depreciation rates reflect the nature of real estate markets. Bokhari & Geltner (2018) examine the age–asset price relationship for commercial real estate across 25 metropolitan areas in the US. They found that depreciation rates vary considerably across metropolitan areas, and point to the moderating role of supply constraints. In addition, Smith (2004) shows that depreciation rates vary within markets. Using granular property data on housing in one US metropolitan area, Smith (2004) finds that depreciation rates vary across local neighborhoods. While such an approach for commercial real estate properties does not seem feasible given the low frequency with which properties are traded, it highlights the importance of including the regional context when examining the age–asset price relationship.

4.3 Empirical methodology

In this section, we discuss our empirical methodology. We adopt the standard hedonic framework to address the age–asset price relationship and calculate average net depreciation rates based on sales data. We relate the logarithm of the sales price to age and a set of property-specific controls. That is P_{ijt} , the sales price of property i in region j and year t , in the baseline model is given by:

$$\log(P_{ijt}) = \alpha + \beta_1 A_{it} + \beta_2 A_{it}^2 + \sum_{k=1}^K \phi_k X_{kit} + \sum_{m=1}^M \delta_m D_{mi} + \gamma_t + \mu_j + \epsilon_{ijt}, \quad (4.1)$$

where A_{it} is the age of a property; X_{kit} is a set of property characteristics ($k = 1, 2, \dots, K$); D_{mi} a set of dummy variables for construction cohorts; and γ_t and μ_j are year and location fixed effects, respectively. ϵ_{ijt} is an i.i.d. error term. $\alpha, \beta_1, \beta_2, \phi_k, \delta_m, \gamma_t$ and μ_j are the coefficients to be estimated.

Equation (4.1) information that can be used to determine the average net depreciation rate, or $\partial P_t / \partial A$. Equation (4.1) includes a polynomial to capture nonlinear depreciation rates with age since assets may have higher depreciation rates in the early years (Chinloy, 1977; Hulten & Wykoff, 1981; Shilling et al., 1991). The estimates for depreciation rates based on Equation (4.1) are calculated as:

$$\hat{D} = \partial P_t / \partial A = \beta_1 + 2 \times \beta_2 A_{it}. \quad (4.2)$$

Further, we will compute standard errors using the delta method.

The estimates for net depreciation rates are based on a comparison with similar properties. We use a set of characteristics to control for observed heterogeneity in sales data. First, we include the size of a commercial property. Larger properties usually have a higher price. Second, we include information on the specific location and whether the property is located in a central business district (CBD) or a major city. Commercial properties located in a CBD or a major city usually sell for higher prices. Third, we include the characteristics of the buyer and the seller to control for any differences in market behavior that may impact on the age–price relationship (Bokhari & Geltner, 2011).

These estimates for depreciation rates may be biased for various reasons. First, omitting the construction year of the property may overlook possible ‘vintage’ effects (Smith, 2004). Investors may have specific preferences for properties in terms of construction years or periods, and building qualities. If the construction year is not included as a factor, any vintage effect will be subsumed in the age coefficients and thus the estimated depreciation rate will be biased. Clearly, multicollinearity issues would be present if we were to include both age and construction year in combination with sales year. To avoid this issue, we follow Smith (2004), Wilhelmsson (2008) and Francke & Van de Minne (2017), and categorize the construction year into vintage cohorts.

Second, using sales prices as a dependent variable may lead to underestimates of the depreciation rate because sales prices capture both land values and structure values as discussed in Section 4.2. It is not easy to remove land values from sales prices as was shown by Francke & Van de Minne (2017) for housing stock. For our current study on commercial real estate depreciation rates, this issue is probably less important as land values are often a smaller share of the sales price of commercial real estate. The sector for which this assumption is perhaps rather doubtful is industrial real estate, as such properties are rather different in nature, and land values tend to be relatively greater than with office and retail real estate. We will therefore present estimates by market segment.

Third, unobserved capital expenditures may lead to downward-biased estimates of the actual depreciation rates. While this is a genuine concern, we would expect these future costs to be capitalized in observed sales prices. Further, our data include mainly investor-focused properties which are typically well-maintained. While the historical building costs of properties might not be observable, investors are well-informed buyers and have access to information on capital expenditure estimates. Depreciation rates that are calculated on the basis of sales prices in the absence of information on capital expenditures, are net depreciation rates.

Indeed, the main estimates we will present are net depreciation rates. Also, to address the concerns raised, we will present *relative* net depreciation rates across regional markets across Europe. That is, we will provide estimates of depreciation rates relative to a baseline, for which we take the UK since it is one of investors' broadest and deepest property markets in Europe. The main benefit of these relative measures is that we implicitly downplay the importance of our assumptions regarding comparable properties, land value shares, capital expenditures, and survival rates. So, even if our original estimates for absolute levels of depreciation rates are downward-biased, we can still perform a useful comparison of relative net depreciation rates between regions.

The model deduces country-specific relative net depreciation rates by augmenting our baseline model in Equation (4.1) with interactions between age and country.

Specifically, the country model becomes:

$$\begin{aligned} \log(P_{ijt}) = & \alpha + \beta_1 A_{it} + \beta_2 A_{it}^2 + \sum_{n=1}^N \theta_{1n} C_{ni} * A_{it} + \sum_{n=1}^N \theta_{2n} C_{ni} * A_{it}^2 + \sum_{k=1}^K \phi_k X_{kit} \\ & + \sum_{m=1}^M \delta_m D_{mi} + \gamma_t + \mu_j + \epsilon_{ijt}, \end{aligned} \quad (4.3)$$

where C_{ni} is the set of dummy variables for countries ($n = 1, 2, \dots, N$) where a property i is located. Equation (4.3) provides estimates relative to the reference country such that θ_{1n} and θ_{2n} capture regional variations in the relative net depreciation rates. The depreciation rate for the reference country is based on β_1 and β_2 .

We further investigate the interplay with economic drivers by augmenting the country model with regional economic drivers. The model then becomes:

$$\begin{aligned} \log(P_{ijt}) = & \alpha + \beta_1 A_{it} + \beta_2 A_{it}^2 + \sum_{l=1}^L \theta_{1l} M_{lit} * A_{it} + \sum_{l=1}^L \theta_{2l} M_{lit} * A_{it}^2 + \sum_{k=1}^K \phi_k X_{kit} \\ & + \sum_{m=1}^M \delta_m D_{mi} + \gamma_t + \mu_j + \epsilon_{ijt}, \end{aligned} \quad (4.4)$$

where M_{lit} represents the set of regional macroeconomic factors ($l = 1, 2, \dots, L$) that a commercial property i is facing in year t ; the interaction terms, $M_{lit} * A_{it}$ and $M_{lit} * A_{it}^2$, capture how depreciation rates vary with regional economic drivers. Note that we demean M_{lit} to facilitate interpretation.⁵⁶

4.4 Data

We use the RCA-Europe commercial property dataset in conducting our empirical analysis.⁵⁷ This dataset contains detailed information of 60,675 commercial property sales across Europe from 2003 to 2017, including sales price, size, address, construc-

⁵⁶From Equation (4.4), we can see that the scale of the variation in depreciation rates changes with the values of the regional economic drivers. To facilitate interpretation, we demean all the regional economic drivers so that the variation of depreciation rates is easier to visualize and discuss since the values of the regional economic drivers then equal their means.

⁵⁷RCA is a company that collects commercial real estate sales data and focuses on commercial real estate properties that are of interest to global institutional investors. The company indicates that the commercial properties included in the RCA-Europe dataset are homogeneous in their attractiveness and accessibility to global institutional investors. As such, the commercial property sales used in this paper are comparable even though they are collected from various sources across European countries.

tion year, year of sale, and type of property. We carefully selected 17,158 sales for which we have sales price information confirmed by at least 2 independent sources for further analysis. As such, we exclude sales where the information is based on appraisal, approximation, and rumors. While this results in a substantially smaller set of observations, this is outweighed by the benefit of using confirmed and thus reliable sales data. We then removed a further 7,364 sales which have incomplete information on property characteristics. We also exclude 891 sales that are part of a larger portfolio sale because their sale prices may be set differently and based on unobserved factors. Further, only sales where the sale price is between the 1st and 99th percentiles of the entire price distribution and the building is less than 150 years old at the time of sale are included, bringing the sample down to 8,234 sales. Finally, a further 7 sales were excluded because we could not find any information on regional economic drivers. This filtering process eventually resulted in a set of 8,227 sales across 16 European countries used in our empirical analysis.

Table 4.1 presents information on the distribution of commercial property sales in each European country. The UK has the highest number of sales in our sample (2,877) and accounts for about 35% of the total number of sales. Denmark (64) and Norway (93) have the fewest sales. The Netherlands has the lowest average price per square feet at about 214 euros per square feet. The most expensive average prices per square feet were found in France (EUR 541) and the UK (EUR 512). The sales data includes properties constructed over an extensive period. Across all sales, the properties in our dataset in Poland were the newest, with a mean construction year of 2004. The country with the oldest properties on average sold was Denmark where the mean construction year was 1961. Sales also varied by typical locations. More than 70% of the sales in Austria, Czech Republic, and Ireland were located in major cities whereas less than 25% of the sales in the Netherlands, Switzerland, and UK were similarly located. The sales were divided into three market segments based on their function: office, retail, and industrial.⁵⁸ Office sales make up more than half of the total sales in every country except Spain. Retail sales are generally the second largest category in most countries, with relatively few industrial sales. Figure 4.1 sh-

⁵⁸ About 59.3% of our observations relate to office sales, 14.3% of them are industrial sales and the remaining 26.4% retail outlets.

Table 4.1: Distribution of commercial properties per country

Country	Number of transactions	Avg. sale year	Avg. price per sqft	Avg. Construction year	% in major city	% Industry	% Office	% Retail
Austria	110	2010	229.017	1986	73	5	65	30
Belgium	200	2012	262.365	1991	55	12	70	18
Czech Republic	118	2012	246.843	1999	72	10	60	30
Denmark	64	2013	347.264	1961	47	10	56	34
Finland	156	2010	249.573	1984	34	15	53	32
France	1,214	2012	541.334	1979	31	8	77	16
Germany	1,128	2012	249.830	1988	49	10	59	31
Ireland	103	2015	497.067	1996	81	7	68	25
Italy	297	2011	333.255	1980	46	11	55	34
Netherlands	472	2013	214.091	1991	23	23	58	19
Norway	93	2012	329.294	1982	53	10	66	24
Poland	186	2012	238.206	2004	39	13	54	33
Spain	228	2012	368.544	1992	44	11	41	47
Sweden	578	2011	240.862	1973	31	21	54	24
Switzerland	403	2011	355.716	1974	23	21	54	25
United Kingdom	2,877	2012	512.054	1985	21	17	55	28
Total	8,227							

Note: This table presents the distribution of commercial properties included in our dataset in each European country. The average price per square foot is based on the nominal price. The term “major city” refers to just the capital city of many countries, but with several exceptions. For Germany, the major cities include Berlin, Cologne, Dusseldorf, Frankfurt, Hamburg, Munich and Stuttgart. For Italy, the major cities are Rome and Milan. For Spain, both Barcelona and Madrid are considered as major cities. For Switzerland, the major cities are Zurich and Geneva.

Figure 4.1: Number of commercial property sales by age

Note: This figure shows the number of sales of each age of all sales (i.e., pooled) and individual market segments (office, retail, and industrial). More than 700 sales occurred of buildings at age 0, i.e., in the year of construction.

ows the number of sales of real estate at each age for all sales (pooled) and for each segment (office, retail, and industrial). It is noteworthy that more than 700 observations are sales with an age of zero, i.e. sales taking place in the year of construction. Further, more than 80% of all the sales in all segments are of buildings less than 50 years old.

Table 4.2 provides summary statistics of property characteristics for all commercial property sales and for sales in each segment. The average selling price of all the commercial property sales in our dataset is about 52 million euros. Office sales have the highest average price (about 58 million euros), while industrial sales have the lowest average price at about 25 million euros. The average size of the properties sold was 177,384 square feet. Industrial properties were the largest on average, while office properties the smallest. The average sales price per square feet of all the properties was about 398 euros, with a standard deviation of about 459 euros. Office properties have the highest average price per square feet, almost four times that of industrial properties. The average age of the properties in our observations at the date of sale is about 28 years, and the mean construction year 1984. Of the three segments, industrial properties were, on average, the newest.

About 33.6% of all our observations are located in CBD areas and 32% of them are located in a major city. Almost half of office properties are located in a CBD or major city, while only around 15% retail properties and less than 10% industrial properties are located in a CBD or a major city. The characteristics of buyers and sellers are quite similar. Across all sales, 41.9% of the sellers were institutional investors as were 55.7% of buyers. Private investors were behind 25.2% of sales and 19.0% of purchases, and public investors 17.4% of sales and 18.4% of purchases. This dominance by institutional investors is even more pronounced in the largest, office, sector. Furthermore, about 90% of these commercial properties bought are for investment purposes.

As outlined earlier, one focus of our paper is to determine regional economic drivers that are related to depreciation. To this end, we gathered information on disposable income⁵⁹, real GDP⁶⁰, and unemployment rate for every NUTS 3 region⁶¹ from 2003 to 2017.⁶² Real GDP is used to reflect the regional production of a NUTS 3 region, disposable income to reflect regional living standards, and unemployment rate as a measure of the regional employment situation. We combine these economic drivers with our commercial property sale data so that every sale is matched with its corresponding NUTS 3 region's economic drivers in the year of sale. Table 4.3 provides the summary statistics of these economic drivers for each country.⁶³ Poland had the lowest average disposable income per household, and Switzerland the highest. UK has the second highest average disposable income per household but also the largest standard deviation which means there are greater disparities in disposable income among NUTS 3 regions in the UK. As with disposable income, Poland also has the lowest average real GDP. Spain has the highest average real GDP (40,555.570 million euros) with a standard deviation of 34,607.480 million euros. Spain also has

⁵⁹Here, disposable income refers to the disposable income per household. It is calculated in real terms based on 2015 and presented in thousand-euro multiples.

⁶⁰Real GDP is shown in million-euro multiples at 2015 prices.

⁶¹NUTS (Nomenclature of Territorial Units for Statistics) is a geocode standard for referencing the subdivisions of countries for statistical purposes. The NUTS classification, going from the broadest level to the most granular level, contains NUTS 1 level, NUTS 2 level, NUTS 3 level and local administrative units (LAUs). The NUTS 3 level is the lowest level for which we could obtain information on regional economic drivers.

⁶²All our data on disposable income, real GDP, and unemployment rates come from Oxford Economics.

⁶³Note that economic drivers of NUTS 3 regions are only calculated for years in which there is at least one sale.

Table 4.2: Summary statistics of commercial property sales

	Pooled		Office		Retail		Industrial	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Price (in million euros)	52.017	64.916	58.057	69.193	53.276	65.794	24.716	27.133
Price per sqft (in euros)	397.821	459.412	463.347	406.356	406.227	604.967	111.338	126.257
Age	27.830	31.994	31.177	34.222	25.437	30.427	18.400	21.193
Construction Year	1984	31.990	1981	34.251	1986	30.225	1994	21.326
Size (in 1,000 sqft)	177.384	230.679	144.351	159.160	186.547	213.463	297.117	404.669
CBD (1=yes)	0.336		0.482		0.158		0.060	
In major city (1 = yes)	0.320		0.454		0.145		0.085	
Seller type								
Institutional	0.419		0.473		0.360		0.309	
Private	0.252		0.225		0.288		0.294	
Public	0.174		0.166		0.212		0.137	
User/Other	0.155		0.136		0.139		0.260	
Buyer type								
Institutional	0.557		0.570		0.558		0.500	
Private	0.190		0.201		0.185		0.159	
Public	0.184		0.164		0.194		0.249	
User/Other	0.069		0.065		0.064		0.093	
Buyer objective								
Investment	0.906		0.888		0.929		0.936	
Occupancy	0.015		0.016		0.004		0.026	
Redevelopment	0.035		0.045		0.017		0.024	
Renovation	0.045		0.050		0.050		0.014	
Number of observations	8,227		4,876		2,172		1,179	

Table 4.3: Summary statistics of economic drivers per country

	Disposable income		Real GDP		Unemployment rate	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Austria	49.267	3.965	65,389.980	33,614.360	8.003	2.575
Belgium	45.958	6.768	51,957.360	28,872.160	12.132	5.574
Czech republic	24.358	3.440	32,946.890	12,789.760	3.280	1.618
Denmark	46.554	2.904	41,071.680	10,472.300	7.455	1.713
Finland	48.677	4.382	60,251.230	31,804.850	6.846	1.450
France	53.860	6.470	121,218.300	71,284.810	8.689	1.733
Germany	43.424	7.486	50,497.480	42,680.870	6.553	3.216
Ireland	60.791	4.381	86,958.860	26,731.130	8.908	2.195
Italy	50.974	5.526	112,550.800	66,979.280	6.925	3.069
Netherlands	44.351	2.779	52,525.840	34,509.470	5.787	1.565
Norway	65.359	7.425	41,569.600	19,418.050	4.064	1.004
Poland	19.383	2.919	26,380.980	20,836.930	5.108	3.315
Spain	43.177	7.112	130,769.400	81,066.500	15.264	6.199
Sweden	48.994	5.867	85,608.290	47,732.220	7.262	1.186
Switzerland	100.316	7.992	61,675.360	42,718.350	5.006	1.810
United Kingdom	83.926	35.551	40,555.570	36,607.480	6.494	2.448

Note: This table presents the means and standard deviations of disposable income, real GDP, and unemployment rate for each European country from 2003 to 2017. Both disposable income and real GDP are calculated based on values adjusted to 2015 prices. Economic drivers are only calculated for NUTS 3 regions with at least one sale in each year.

the highest average unemployment rate at about 15.3%. The average unemployment rate in Czech Republic is the lowest at about 3.3%. As discussed in Section 4.3, these regional economic drivers are demeaned for further empirical analysis.

4.5 Empirical results

In this section, we report the results of regression analyses for Equations (4.1), (4.3) and (4.4). We first investigate the average net depreciation rates of all 16 European countries, and explore the heterogeneity of depreciation in different market segments. Subsequently, we deduce country-specific relative net depreciation rates by focusing on each market segment. Finally, we connect depreciation rates to regional economic drivers and discuss how depreciation rates vary with these economic drivers in each market segment.

4.5.1 Depreciation rates across Europe

Table 4.4 presents the regression results for depreciation rates from Equation (4.1) using the pooled and sector data separately. Column (1) shows the regression results using all the sales data. Age and Age² are the key variables to focus upon. Here, we see that the Age coefficient is negative, while the Age² coefficient is positive. This combination means that the values of commercial properties depreciate with age, but at a declining speed. Using Equation (4.2), we are able to calculate the depreciation rate of properties of different ages. A one-year-old commercial property has a depreciation rate of 1.17%. The depreciation rate declines to 1.11% for a seven-year-old commercial property.⁶⁴ The coefficients of the control variables show the expected signs. When the size of a commercial property increases by 1%, the sales price increases by 0.738%. The sales prices of properties located in CBD zones or major cities are 48.2% and 44.2% higher respectively than properties located outside these areas.

Columns (2), (3), and (4) show the regression results for office, retail, and industrial properties respectively. Some differences among the three market segments can be observed for the control variables. The sales prices of office properties are the most sensitive to changes in property size. That is, if the size of an office property increases by 1%, its sales price increases by 0.898%. For both office and retail properties, being located in a CBD zone significantly increases sales prices by about 38.3% and 32.9% respectively compared with other locations. However, for industrial properties there is no statistically significant price difference related to location. On a note of caution, this may be because there are very few industrial properties located in CBD zones making it difficult to identify variations. However, industrial properties located in a major city do see a premium over those located elsewhere: their sales prices are 27.3% higher, although this premium is less than that for both office and retail properties.

Looking at the coefficients for Age and Age² in Columns (2), (3), and (4), we see that all three market segments show a similar depreciation pattern to the pooled data. That is, all three columns have a negative Age coefficient and a positive Age²

⁶⁴Seven years was picked as an example because investors typically hold onto a commercial property for seven to ten years.

Table 4.4: The standard regression results of depreciation

	(1)	(2)	(3)	(4)
	Pooled	Office	Retail	Industrial
Age	-0.0119*	-0.0210***	-0.00345	-0.0237***
	(0.00566)	(0.00566)	(0.00514)	(0.00671)
Age ²	5.54e-05**	9.50e-05***	2.84e-05	6.87e-05
	(2.49e-05)	(2.41e-05)	(2.08e-05)	(5.52e-05)
Log of size	0.738***	0.898***	0.761***	0.739***
	(0.0114)	(0.0252)	(0.0278)	(0.0193)
CBD (1=yes)	0.482***	0.383***	0.329***	0.0607
	(0.103)	(0.0694)	(0.0422)	(0.0918)
In major city (1 = yes)	0.442***	0.427***	0.436***	0.273***
	(0.0870)	(0.0868)	(0.0886)	(0.0782)
Construction cohorts	yes	yes	yes	yes
Property characteristics	yes	yes	yes	yes
Seller characteristics	yes	yes	yes	yes
Buyer characteristics	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Location fixed effects	yes	yes	yes	yes
Number of observations	8,227	4,876	2,172	1,179
Number of regressors	51	51	51	51
RSS	3488.976	1445.691	779.494	258.014
Adjusted R-squared	0.608	0.728	0.662	0.658

Note: The dependent variable is the log of sales price. Clustered standard errors at the country level are shown in parentheses. The same variables are used in the regressions in each column. Chow tests suggest that the coefficients are not statistically consistent across market segments. Further information can be obtained from the authors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

coefficient, as was the case with the pooled regression in Column (1). Nevertheless, properties in the three market segments do depreciate at different speeds. Industrial properties depreciate most quickly, and retail properties the slowest.⁶⁵ The retail properties depreciate so slowly that the Age and Age² coefficients in Column (3) are insignificant, which means that, at least statistically, the depreciation rate of retail properties is non-different from zero. The Age² coefficient in column (4) is also insignificant.

⁶⁵Further discussion on the comparison of depreciation rates among the three market segments can be found in Appendix 4.A.

One of the most important assumptions when regressing a pooled dataset is that the coefficients are consistent for all the data. However, the coefficients we obtained for the key Age variables and for the control variables all suggest that the different market segments have different coefficients for certain variables. Given this suggestion, we use a Chow test to statistically check the consistency of the coefficients. The resulting Chow test statistic (32.061) rejects the null hypothesis of coefficient consistency across market segments.⁶⁶ This result suggests that one should consider each market segment separately rather than pooling the data. Therefore, in the following empirical analysis, we no longer present pooled regression results.

As discussed above, we present relative net depreciation rates across regional markets across European countries. Table 4.5 shows regression results based on Equation (4.3) including an Age and Country interaction term. UK is used as the reference country because it has one of the broadest and deepest property markets in Europe. The Age and Age² coefficients in Table 4.5 capture the UK depreciation rates, while the coefficients of the Age and Country interaction terms reflect the difference in depreciation rates between the reference country (UK) and other countries. As with the results in Table 4.4, the Age and Age² coefficients suggest declining depreciation rates for properties in all three market segments in the UK. Where the Age and Country interaction terms are significant, this is an indication that the depreciation rates in these countries are significantly different from the reference country. To illustrate regional variations in depreciation rates more clearly, we calculate the depreciation rates for all three market segments in each country and present the results in Figure 4.2.

Figure 4.2 shows the depreciation rates and associated 95% confidence intervals for properties that are seven-year-old in each country. Office, retail, and industrial properties are presented in Panels A to C respectively. Countries with only a few (less than 25) sales in a market segment are marked in red because the limited data make the findings less certain. From Figure 4.2, it is apparent that depreciation rates vary across European countries. The depreciation rate of a seven-year-old office building in the UK is about 1.6% with the 95% confidence interval ranging from

⁶⁶Note that the same variables are used in the regressions in Columns (1) to (4). Details of the Chow test calculation can be obtained from the corresponding author.

Table 4.5: Depreciation variations across European countries

	(1)	(2)	(3)
	Office	Retail	Industrial
Age	-0.0170*** (0.00415)	-0.00753* (0.00385)	-0.0219*** (0.00567)
Age ²	6.63e-05*** (1.13e-05)	4.65e-05** (1.98e-05)	6.70e-05* (3.76e-05)
Austria*Age	-0.0136*** (0.00101)	0.0104*** (0.00200)	-0.0290** (0.0109)
Austria*Age ²	9.64e-05*** (6.56e-06)	-0.000103*** (1.83e-05)	0.000581* (0.000284)
Belgium*Age	-0.00538*** (0.00125)	-0.0106** (0.00417)	-0.00790 (0.00644)
Belgium*Age ²	-6.68e-06 (1.01e-05)	0.000285*** (9.39e-05)	0.000324* (0.000153)
Czech republic*Age	0.00255 (0.00438)	0.0206*** (0.00358)	-0.0299*** (0.00538)
Czech republic*Age ²	-2.27e-05 (4.01e-05)	-0.000184*** (3.13e-05)	0.000244 (0.000146)
Denmark*Age	-0.0270*** (0.00102)	-0.00345 (0.00208)	-0.129*** (0.0130)
Denmark*Age ²	0.000173*** (8.98e-06)	-1.36e-05 (1.84e-05)	0.00215*** (0.000239)
Finland*Age	-0.00835*** (0.00129)	-0.0101*** (0.00135)	-0.0132** (0.00491)
Finland*Age ²	5.06e-05*** (9.94e-06)	7.73e-05*** (1.72e-05)	0.000207*** (6.38e-05)
France*Age	0.00776*** (0.000762)	0.0207*** (0.00142)	0.0145*** (0.00194)
France*Age ²	-4.67e-05*** (2.61e-06)	-0.000107*** (7.56e-06)	-3.16e-06 (4.15e-05)
Germany*Age	-0.00792*** (0.000370)	0.00236* (0.00120)	-0.00656*** (0.00158)
Germany*Age ²	4.97e-05*** (4.03e-06)	2.84e-07 (1.18e-05)	2.00e-05 (2.42e-05)
Ireland*Age	0.00367** (0.00142)	0.0155*** (0.00320)	-0.709*** (0.0229)
Ireland*Age ²	-4.17e-05*** (1.29e-05)	-0.000140*** (2.23e-05)	0.0268*** (0.000919)
Italy*Age	-0.00781*** (0.00108)	0.000446 (0.00313)	0.0132*** (0.00249)

Italy*Age ²	8.64e-05*** (8.19e-06)	5.09e-05** (2.35e-05)	-0.000112*** (2.86e-05)
Netherlands*Age	-0.0230*** (0.00105)	0.0197*** (0.00246)	-0.0125*** (0.00198)
Netherlands*Age ²	0.000173*** (9.16e-06)	-0.000125*** (1.65e-05)	0.000226*** (4.71e-05)
Norway*Age	-0.00938*** (0.000927)	-0.0105*** (0.00188)	-0.00810** (0.00361)
Norway*Age ²	5.81e-05*** (7.26e-06)	7.81e-05*** (1.20e-05)	6.80e-05 (5.93e-05)
Poland*Age	-0.0140*** (0.00236)	0.00125 (0.00441)	0.128*** (0.0110)
Poland*Age ²	0.000107*** (1.74e-05)	-1.67e-05 (7.00e-05)	-0.00896*** (0.000873)
Spain*Age	0.0140*** (0.00249)	0.000982 (0.00423)	-0.0690*** (0.00778)
Spain*Age ²	-0.000112*** (1.69e-05)	0.000112*** (3.60e-05)	0.00310*** (0.000398)
Sweden*Age	-0.0140*** (0.000268)	0.00292** (0.00131)	0.00373* (0.00198)
Sweden*Age ²	0.000102*** (4.10e-06)	-4.15e-05*** (1.16e-05)	-6.71e-06 (2.95e-05)
Switzerland*Age	-0.0113*** (0.000817)	0.00554*** (0.00100)	0.00184 (0.00267)
Switzerland*Age ²	9.31e-05*** (6.05e-06)	-7.10e-05*** (8.74e-06)	-2.13e-07 (3.50e-05)
Construction cohorts	yes	yes	yes
Property characteristics	yes	yes	yes
Seller characteristics	yes	yes	yes
Buyer characteristics	yes	yes	yes
Year fixed effects	yes	yes	yes
Location fixed effects	yes	yes	yes
Observations	4,876	2,172	1,179
Adjusted R-squared	0.736	0.672	0.671

Note: Dependent variable is log of sales price. Column (1), (2) and (3) shows the regression results using office, retail and industrial properties respectively. Interaction terms of age and country are included to capture the regional variation in depreciation rates. The UK was chosen as the reference country as it is one of the broadest and deepest property investment markets in Europe. Clustered standard errors at country level are shown in parentheses. Other information can be obtained from the authors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 4.2: Depreciation rates and confidence intervals across Europe

Note: This figure shows the depreciation rates and corresponding 95% confidence intervals for seven-year-old properties in each segment. If the number of sales in a market segment is below 25 in total, the depreciation rate point is colored red.

about 0.8% to 2.5%. For office properties of the same age, Denmark has the highest depreciation rate of almost 4.1%, while Spain shows the lowest depreciation rate of about 0.4%. For retail properties, regional variations are even more obvious. The UK has a depreciation rate of about 0.7% for a seven-year-old retail property and the depreciation rates of similar retail properties in Belgium, Denmark, Ireland, and Norway are also all below 1%. Not only do similar retail properties in Czech Republic, France, and the Netherlands shows no evidence of depreciation, their value increases with age and this effect is significantly different from zero. Industrial properties generally show higher depreciation rates than office and retail properties. Regional variations in the depreciation rates of industrial properties can also be clearly observed. Most notably, the depreciation rates of a seven-year-old industrial property in Denmark and Ireland are about 11% and 30% respectively, far higher than in other European countries. However, on a note of caution, this finding may be due to there being very few industrial property sales in these two countries in our dataset.

From Table 4.5 and Figure 4.2, we can see that the depreciation rates in European countries show clear regional variations. The depreciation rates of commercial properties vary depending on which country they are located in and in which market segment they belong. However, at this stage, it is unclear how these correlate with macroeconomic drivers. To explore this question further, we extend this research to link commercial property depreciation rates to regional economic drivers. The results are presented and discussed in the next section.

4.5.2 Depreciation rates and regional economic drivers

We further explore the regional variations in depreciation rates across Europe by investigating the association with regional economic drivers. To this end, three regional economic drivers, disposable income, real GDP, and unemployment rate, were selected. These economic drivers are available for all NUTS 3 regions and could be combined with our commercial property sale data. We multiply the demeaned values of these economic drivers by the Age and Age² coefficients to facilitate interpretation.

Table 4.6 shows the regression results from Equation (4.4), with columns (1) to

Table 4.6: Economic drivers and depreciation

	(1)	(2)	(3)
	Office	Retail	Industrial
Age	-0.0198*** (0.00363)	-0.00249 (0.00466)	-0.0199** (0.00676)
Age ²	0.000100*** (1.74e-05)	2.08e-05 (2.80e-05)	3.66e-05 (7.96e-05)
Disposable income*Age	5.50e-05* (2.64e-05)	-0.000105 (6.74e-05)	0.000151*** (4.90e-05)
Disposable income*Age ²	-5.15e-07** (2.09e-07)	3.48e-07 (5.24e-07)	-9.86e-07 (6.49e-07)
Real GDP*Age	4.93e-08*** (1.50e-08)	3.32e-08 (4.61e-08)	1.35e-08 (6.19e-08)
Real GDP*Age ²	-2.64e-10* (1.30e-10)	-6.67e-11 (3.12e-10)	8.72e-11 (7.22e-10)
Unemployment rate*Age	0.000572* (0.000295)	-0.000121 (0.000706)	0.00156*** (0.000484)
Unemployment rate*Age ²	-6.02e-06** (2.17e-06)	3.71e-06 (4.55e-06)	-1.08e-05** (4.36e-06)
Real GDP	2.58e-06* (1.41e-06)	9.80e-07* (5.48e-07)	1.37e-06* (7.30e-07)
Disposable income	0.00830*** (0.000628)	0.0130*** (0.00238)	0.0131*** (0.00113)
Unemployment rate	-0.000840 (0.0106)	0.00196 (0.0105)	0.00366 (0.00792)
Construction cohorts	yes	yes	yes
Property characteristics	yes	yes	yes
Seller characteristics	yes	yes	yes
Buyer characteristics	yes	yes	yes
Year fixed effects	yes	yes	yes
Location fixed effects	yes	yes	yes
Observations	4,876	2,172	1,179
Adjusted R-squared	0.786	0.687	0.693

Note: The dependent variable is log of sales price. The values of the economic drivers are demeaned before being multiplied by Age and Age² to facilitate the interpretation of the economic drivers' influence on depreciation. Clustered standard errors at country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

(3) reporting office, retail and industrial properties respectively. The Age coefficients are quite similar to those in Table 4.4, suggesting that the regional economic drivers

do not radically alter the age coefficients on which we based depreciation rates. Both real GDP and disposable income are positively correlated with asset prices for all three market segments. In Column (1), all three Age and economic driver interaction terms are significant, meaning that all the economic drivers have some influence on the depreciation rates of office properties. By combining the coefficients of the Age and interaction terms, one can conclude that there are negative relationships between the depreciation rate of office properties and local economic drivers. In other words, when the values of the economic drivers are higher, the depreciation rates of office properties are lower. That is, office properties in NUTS 3 regions with stronger economic drivers will depreciate at a lower rate.

Compared to office properties, the results for retail properties suggest quite different patterns. The coefficients in Column (2) indicate that retail properties do not show a consistent trend in their depreciation and that no significant relationship between economic drivers and depreciation rates can be identified for retail properties. Only real GDP and disposable income have positive relationships with the sales price of retail properties. From Column (3), we can see that disposable income and unemployment rate, but not real GDP, influence the depreciation rate of industrial properties. As with office properties, industrial properties located in NUTS3 regions with higher disposable income and unemployment rates will depreciate at a lower speed.

4.6 Conclusion

In this paper we report our investigation into the asset age–sales-price relationship of commercial properties across regional markets in Europe. We use the asset age–price relationship to calculate depreciation rates for commercial properties in the office, retail, and industrial sectors separately. We argue that our methodology, given the absence of precise data on land values, capital expenditures, and survival rates, provide reliable estimates of *relative net depreciation rates* that allow useful comparisons across regional markets in Europe. Further, we have investigated the interplay of variations in depreciation rates and in regional economic drivers.

For these purposes, we used a comprehensive commercial property sales database

covering 16 European countries from 2003 to 2017. Our estimates for net depreciation rates are based on a comparison of similar properties. The methodology employs a linear price model with a quadratic specification of age and a set of control variables. The controls address the observed heterogeneity in property and location, sales year, and buyer and seller characteristics. The coefficients for age and age squared are used to calculate net depreciation rates.

In the first stage, we investigated differences in depreciation rates across countries in Europe and found substantial cross-sectional variations in depreciation rates across market segments and countries. On the basis of a model combining data from all the countries, we concluded that retail properties had the lowest net depreciation rate and industrial properties the highest. We also found that depreciation rates for the individual market segments vary across countries. A note of caution when interpreting these differences is that for some segments and countries there were very few sales of commercial properties in certain segments or years meaning that the statistics could be skewed by a few outliers. Nevertheless, we find - when compared to the UK - that many other European countries show different depreciation rates in various market segments.

As the second step in our analysis, we examined the interplay between depreciation rates and regional economic drivers. For this, we augmented the linear price model with data on regional economic drivers reflecting economic production, employment, and household living standards. We concluded that including these regional economic drivers did not significantly change the age-related coefficients from which we calculated depreciation rates. We found that both regional production (based on real GDP) and regional living standards (using disposable income) are positively correlated with asset prices for all three market segments. The depreciation rates of office properties were negatively correlated with all three economic drivers whereas, for industrial properties, only disposable income and unemployment rate had significant negative relationships with depreciation rates. For retail properties the influences are less clear as the interaction terms were statistically insignificant.

Our main contribution to the existing literature is that we have investigated regional variations in the depreciation rates of commercial properties across Europe

using one of the most comprehensive dataset available. We have been able to present relative net depreciation rates for most investor markets across Europe. We have also explored interrelationships with regional economic drivers on the basis that investors use these regional data to decide where to invest. One concern, however, is that the methodology here has a stylized character. First, as Bokhari & Geltner (2018) noted, the survival rate of a property is an important factor in determining depreciation rates. If the survival rate is not considered, the calculated depreciation rate may be biased. While we have argued that the survival rates of commercial property in Europe are likely to be fairly constant, a more formal investigation into this aspect would be a logical step for future research. Further, if the data allow, a useful refinement to the model specification would be to incorporate economic conditions and business cycles in a more comprehensive approach given that not only a building's age but the calendar year in which it is bought and sold influence the depreciation rate.

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Appendix 4.A Average age-price profile of commercial properties

To show how the sales price of a commercial property depreciates with age, we illustrate the average age-price profile of pooled, office, retail, and industrial properties in Figure 4.3. It is interesting to note that, when considering all sales, the turning point of the age-profile curve is at age 107, which means the depreciation rate for a commercial property of that age is zero.⁶⁷ The average depreciation rate of a 107-year-old commercial property over its lifetime is about 0.89% per year⁶⁸. For office properties, the turning point is around the age of 111, which is not dissimilar. The average depreciation rate for a 111-year-old office property is about 1.6% per year. For industrial properties, their turning point is at about 172 years, so far beyond that of other types of property. Since the maximum age of the properties in our sample is 150 years, we calculate the average depreciation rate for a 150 year-old industrial property, which is about 1.8% per year. The age-sales price relationship as well as the depreciation rates for retail properties is less clear since the coefficients of the age terms are insignificant. This suggests that retail properties depreciate so slowly that the depreciation rate is statistically no different to zero. The average depreciation rate of retail properties is about 0.25% per year and the turning point is 61 years old.

The different depreciation speeds of different types of property can also be seen in Figure 4.3. Of the different types of properties, the remaining value of retail properties is highest at the same age and the remaining value of industrial properties the lowest. This indicates that industrial properties depreciate the fastest, while retail properties depreciate at the slowest speed. We can conclude that properties in these three market segments do depreciate at different speeds.

⁶⁷As argued by Bokhari & Geltner (2018), the turning point indicates when the value of a commercial property depreciates to zero. That amounts to the end of a commercial property's lifetime.

⁶⁸The depreciation rate is different in each year. We calculate the average depreciation rate of a commercial property as the average of all the previous years' depreciation rates.

Figure 4.3: Average age-price profile of commercial properties

Note: This figure shows the average age-price profile of commercial properties. This figure is constructed using coefficients of Age and Age² in Column (1), (2), (3) and (4) of Table 4.4.

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Chapter 5

The External Effects of Inner-city Shopping Centers: Evidence from the Netherlands

Abstract

Shopping center redevelopment is inevitable to remain attractive for consumers. In this paper, we investigate the external effects of shopping center redevelopment on nearby residential property prices. Using a difference-in-difference empirical framework, we find the redevelopment has positive external effects on nearby property prices. We find the price of a property located next to a redeveloped shopping center increases by 1.43% on average just after redevelopment. Our results indicate that these positive external effects wear off rather rapidly across space and over time. This suggests that shopping center redevelopment plays a substantial, but limited, role in combating neighborhood deprivation.

Keywords: *difference-in-difference, external effects, redevelopment, shopping centers, urban revitalization*

5.1 Introduction

In the 20th century, shopping centers have become an established fact in modern urbanized economies.⁶⁹ These shopping centers are important neighborhood amenities providing goods, services and, increasingly, shopping experience to consumers.

For a shopping center to remain a community center of the neighborhood, a trend toward more extensive and more frequent redevelopment has been observed (Gibbs, 2012).⁷⁰ Shopping centers wear and tear off both physically, functionally and economically, such that “malls built ten years ago are considered mature, those completed fifteen years ago being old, and malls completed twenty years ago being ancient” (Lord, 1985, p. 226). Online shopping has not curbed this trend. On the contrary, it has intensified the need for redevelopment to prevent dead shopping centers.

Redevelopment of a shopping center is, like any urban revitalization project, about internalizing externalities. Owners of shopping centers may be inclined to redevelop outdated shopping centers according to the most recent shopping trends and consumers’ preferences only when private costs are fully covered (Brueckner, 1980; Rosenthal & Helsley, 1994; Munneke, 1996; Brueckner & Rosenthal, 2009). Postponing redevelopment and major maintenance leads to outdated and physically decayed shopping centers (Lord, 1985). As a result, retail vacancy in the shopping center rises and the net rental income of the shopping center declines. To maintain their market position, redevelopment of existing shopping centers seems inevitable (Sternlieb & Hughes, 1981). The redevelopment also affects the attractiveness of the surrounding neighborhood. After redevelopment, on one hand, residents in the neighborhood can enjoy the convenience brought by a renewed and trendy shop-

⁶⁹Shopping centers are those “commercial outlets which have been designed, planned, developed and managed as one single unit”, and are to be distinguished from shopping districts in terms of their single vis-a-vis multiple ownership and management control. Shopping centers can be located inside shopping districts. Unlike in the United States, many shopping centers in Europe are located in urbanized and residential areas.

⁷⁰Redevelopment refers to any revision of the built environment, and synonymous for revitalization, modernization, regeneration, renewal, and urban transformation. We use these terms interchangeably. In this paper, redevelopment of existing shopping centers refers to any major revision of the exterior or interior that “implies physical changes” (Lord, 1985, p. 227). Redevelopment includes a variety of actions, such as (a) expansions or reductions in the floor space of the shopping center, (b) the uplifting and enclosure of previously open shopping areas, and (c) refitting of multiple individual outlets.

ping center; on the other hand, some inconvenience caused by the shopping center, such as noise and traffic congestion, can be relieved. As a result, housing demand in neighborhoods near the redeveloped shopping center is likely to rise and, consequently, the transaction price of nearby residential properties will increase. Because of these external effects, redevelopment is not only of economic interest to shopping center owners, but also to local policy makers.

It is often assumed by policy makers that redevelopment is a tool to combat neighborhood deprivation. Policy makers who wish to revitalize neighborhoods do include social cost considerations and sometimes provide public finance in funding alterations to access and parking, or to public space to let a property owner redevelop their property (Ahlfeldt et al., 2017). A broad set of literature finds evidence for positive external effects from such place-based investments, such as brownfields (Kiel & Zabel, 2001), cultural heritage (Been et al., 2016; Koster & Rouwendal, 2017), industrial heritage (Van Duijn et al., 2016), local parks (Livy & Klaiber, 2016), and subsidized housing (Schwartz et al., 2006; Koster & Van Ommeren, 2019). These empirical studies suggest that property prices tend to be anywhere between 0% and 17% higher in neighborhoods after these investments. However, an important difference is that for most of these studies the decision maker is the (local) government whereas in our paper the decision maker is the owner of a shopping center. The aim of our paper is to explore whether shopping center redevelopment can combat neighborhood deprivation by investigating the external effects of shopping center redevelopment on nearby residential property prices.

We combine residential property transaction data between 1990 and 2014 with data on the location of shopping centers in the Netherlands, the timing of the shopping center redevelopment and other shopping center characteristics. In total, we examine 273 redeveloped shopping centers between 1992 and 2010 to elicit information on the external effects of shopping center redevelopment on surrounding residential property prices. We use a difference-in-difference approach to control for unobserved heterogeneity. Especially, the external effects associated with shopping centers are dynamic in nature. Properties located closer to a redeveloped shopping center are expected to experience higher external effects. Because of the deterioration of shopping centers, the external effects of redevelopment should not persist but

decrease over time. Therefore, we also consider spatial and temporal dimensions of the external effects in our empirical analysis.

The contribution of our study is threefold. First, we examine redevelopment for inner-city shopping centers in the Netherlands. The literature on the impact of shopping center redevelopment is rather absent. One of the reasons is that detailed information on shopping centers and associated redevelopment is often unavailable. Existing studies on retail examine the openings of new stores (Neumark et al., 2008; Pope & Pope, 2015; Zhou & Clapp, 2015). We focus on the redevelopment of existing shopping centers. Second, we provide new insights into the external effects of shopping centers. Based on a comparison of residential property prices before and after redevelopment using a difference-in-difference approach, we examine the external effects of shopping centers on local housing markets. Third, we provide evidence of how these external effects evolve across space and over time. We incorporate spatial and temporal (interaction) variables to capture the dynamics of external effects, allowing for spatial and temporal changes in the external effects after redevelopment. A similar approach is used in Schwartz et al. (2006), Van Duijn et al. (2016) and Been et al. (2016). Our findings indicate that, before redevelopment, residential properties located within 1,000 *m* of shopping centers sell for less than comparable properties located further away from shopping centers. After redevelopment, nearby property prices increase because of the positive external effects caused by the redevelopment. These positive effects wear off across space and over time. The increase of property price caused by the redevelopment vanishes within a few years.

The remainder of this paper is organized as follows. Section 5.2 provides some theoretical background on the redevelopment of shopping centers, the timing of the redevelopment decision and the associated external effects. Section 5.3 introduces the empirical methodology used in our analysis. The data and descriptive statistics are presented in Section 5.4. Section 5.5 reports and discusses our main results. In Section 5.6, we propose various sensitivity analyses. Section 5.7 concludes.

5.2 The redevelopment of shopping centers

We consider a housing market (residential neighborhood) where a shopping center is located. The shopping center provides residents in the neighborhood with the convenience of shopping and easy access to entertainment which increases the attractiveness of the neighborhood (Bloch et al., 1994; Shields, 1995; Rosiers et al., 1996; Koster & Rouwendal, 2012; Kuang, 2017). In contrast, the shopping center may also cause inconvenience (e.g. air pollution, crime, noise and traffic congestion) which decreases the attractiveness of the neighborhood (Hughes & Sirmans, 1992; Smith et al., 2002; Kahn & Schwartz, 2008; Ihlanfeldt & Mayock, 2010; Pope & Pope, 2012; Swoboda et al., 2015; Lens & Meltzer, 2016). The local housing market surrounding the shopping center may experience higher demand for housing if the convenience outweighs the inconvenience. Most of the existing studies argue that the presence of a shopping center is reflected in higher residential property prices in the neighborhood (Sirpal, 1994; Rosiers et al., 1996; Pope & Pope, 2015).

However, shopping centers deteriorate physically, functionally and economically (e.g., facilities may be broken, decorations may fade, consumer demand changes, the entire design may become outdated, and so on) (Williams, 1997; Clapp & Salavei, 2010; Bokhari & Geltner, 2018). Compared to housing, shopping centers deteriorate much faster. A shopping center is considered to be mature after 10 years and ancient after 20 years (Lord, 1985). With the deterioration, retail vacancy in the shopping center starts to rise and the net rental income of the shopping center consequently decreases (Lord, 1985).⁷¹ Meanwhile, the inconvenience may become worse and worse (e.g., crime rate may soar and traffic congestion may worsen). The decision on what to do with the deterioration is taken by the shopping center owner who wants to maximize lifetime profits. In every period, a shopping center owner can decide to leave the shopping center as it is, sell the shopping center or redevelop the shopping center.

Redeveloping the shopping center according to the most recent shopping trends and consumers' preferences is attractive if the expected change in net rental income

⁷¹A shopping center owner may directly be affected if the tenants' rent is linked to the turnover. Lord (1985) discusses that redevelopment efforts – in some cases – have been directly stimulated by the loss of an anchor tenant.

is higher than the private costs of redevelopment. The timing of redevelopment depends on the marginal cost of foregone rental income and the expected marginal benefits of redevelopment (Wong & Norman, 1994). Once the shopping center is redeveloped - updated and adjusted to meet customers' demand - the benefits of the shopping center are restored and likewise the attractiveness of the neighborhood are expected to increase (Chebat et al., 2014). Any inconvenience caused by the deterioration of shopping centers may also be alleviated. For example, traffic congestion could be solved if the roads around shopping centers are restructured and if more parking space is provided. After redevelopment, it is expected that the demand for housing on the local housing market will increase. This implies that residential properties in close proximity to the redeveloped shopping center are expected to sell at higher prices compared to similar properties which are not affected by the shopping center redevelopment. This, in theory, advocates that shopping center redevelopment can be used as a tool to combat neighborhood deprivation. However, over time, the shopping center starts to deteriorate again and, as a consequence, the positive external effects of redevelopment on property prices are expected to decrease.

5.3 Empirical methodology

Our goal is to identify the external effects of shopping centers by considering residential property prices after the redevelopment. External effects are not directly observed so they must be identified in an indirect way. We use residential property prices in the proximity of redeveloped shopping centers for that purpose. We propose to extend the model to cover estimates for heterogeneity in external effects across space and over time. Properties are differentiated by proximity to the redeveloped shopping center and the timing of the sale. This faces us with the challenge to define areas which received external effects (target areas) and which do not (control areas), and to disentangle the external effect of redeveloped shopping centers from other influences that have an impact on residential property prices. We, therefore, pay careful attention to defining target and control areas. We deal with these issues later in this section.

To identify the external effects of redeveloped shopping centers on property prices,

we estimate a difference-in-difference hedonic price model to capture the price change after redevelopment in predefined target and control areas. Specifically, we estimate the following equation:

$$\begin{aligned} \log(P_{ijt}) = & \alpha + \beta_1 Target_i + \beta_2 Target_i \times Distance_i + \beta_3 Target_i \times Trend_t + \beta_4 Target_i \\ & \times Trend_t \times Distance_i + \theta_1 Target_i \times Post_t + \theta_2 Target_i \times Post_t \\ & \times Distance_i + \theta_3 Target_i \times Post_t \times Trend_t + \theta_4 Target_i \times Post_t \times Trend_t \\ & \times Distance_i + \sum_{k=1}^K \phi_k X_{kit} + \gamma_t + \mu_j + \varepsilon_{it}, \end{aligned} \quad (5.1)$$

where $\log(P_{ijt})$ is the log of the price of property i in a (small) geographical area j and in sales year t ; $Target_i$ is a dummy variable indicating whether property i is located in the target area or not; $Distance_i$ is the distance between property i and its nearest redeveloped shopping center; $Trend_t$ is the difference between the year of sale t of property i and the year of completion of the nearest redeveloped shopping center; $Post_t$ is a dummy variable which reflects whether property i is sold after the redevelopment or not (more information about $Target_i$, $Distance_i$, $Trend_t$, and $Post_t$ are described below); X_{kit} represents a set of control variables ($k = 1, 2, \dots, K$) which include structural characteristics of property i in year t , shopping center characteristics of the nearest redeveloped shopping center and characteristics of the neighborhood where the property i is in year t ; γ_t and μ_j are separately year of sale and (small-scale) area fixed effects; ε_{it} is an idiosyncratic error term. The coefficients to be estimated are α , β_{1-4} , θ_{1-4} , ϕ_k , γ_t and μ_j .

Our difference-in-difference approach includes two key variables, $Target_i$ and $Target_i \times Post_t$. We use these variables to investigate the external housing market effects of the shopping center redevelopment. $Target_i$ equals one if property i is in the target area, zero otherwise. It captures the difference in residential property prices between properties located in the target area and those in the control area before the redevelopment of shopping centers. $Target_i \times Post_t$ is the main variable of interest. It equals one if property i is located in the target area and is sold after the redevelopment, zero otherwise. The coefficient of this variable measures the external

effect of the redevelopment of shopping centers on residential property prices in the target area. In our empirical strategy, we initially set our target area to be within 1,000 *m* to the nearest redeveloped shopping center, while the control area is between 1,000 and 2,000 *m*.⁷² To use the outer rings as control areas is not unusual in the literature (see, e.g., Schwartz et al., 2006; Ahlfeldt et al., 2017; Van Duijn et al., 2016; Helmers & Overman, 2017). In our sensitivity analyses, we check the robustness of our coefficients by changing the control area using propensity score matching.

We interact $Target_i$ and $Target_i \times Post_t$ with $Trend_t$. $Target_i \times Trend_t$ is included to identify the temporal heterogeneity of property price difference between target and control areas before redevelopment. It equals property *i*'s year of sale minus the year of redevelopment of the nearest redeveloped shopping center, given that property *i* is sold before the redevelopment and located in the target area. The coefficient can be interpreted as how the property price difference between the target and control area before redevelopment has changed over time. Similarly, $Target_i \times Post_t \times Trend_t$ equals property *i*'s year of sale minus the year of redevelopment if property *i* is located in the target area and is sold after redevelopment. Like $Target_i \times Trend_t$, it suggests how the external effects of the redevelopment of shopping centers on property prices vary over time.

All these variables are interacted with $Distance_i$, which allows us to observe how these effects vary with distance.⁷³ The distance variable is measured by the Euclidean distance between property *i* and the polygon's edge of the nearest shopping center, using Geographic Information System (GIS) techniques.⁷⁴ The polygons for shopping centers are drawn in GIS based on their actual locations, shapes, and sizes, and they reduce measurement error in the distance from properties to shopping centers. This holds particularly for large shopping centers.⁷⁵

To capture the external effects – and its dynamics – that shopping centers have on residential property prices is challenging because the selection of redeveloped shop-

⁷²This is our proposed radius based on previous literature and many of our own sensitivity checks.

⁷³We have checked the nonlinearity of the effect of distance and time. The empirical results showed that the spatial and temporal change of the price effects is very similar to a linear functional form.

⁷⁴We measure distance as Euclidean distance given the very local neighborhoods of within walking distance of our target areas.

⁷⁵In Appendix 5.A, we include an example of a redeveloped shopping center which is located in Amsterdam. By accounting for the shape and size of the shopping center, we minimize measurement error of our distance variable and we show how that affects the predefined target and control area.

ping centers may not be random. Although this problem would be more severe if we focused on newly built shopping centers, it is possible that the decision and timing of redeveloping shopping centers depend on characteristics of properties and neighborhoods. If that were the case, we should be concerned that the external effects of redevelopment are actually reflecting unobserved property and neighborhood characteristics, rather than the external effects themselves. We do not expect such endogeneity issues because our methodology does not depend on the catchment area of the shopping center.⁷⁶ To probe more deeply into this, we check for nonrandom selection of redevelopment in a more formal way in Appendix 5.B by estimating a logit model of redevelopment on neighborhood characteristics. We find – including many control variables – no significant effect of residential property prices on the redevelopment decision of shopping centers.

Next, we propose to run a number of sensitivity analyses to check the robustness of our proposed specification. First, we use alternative specifications to relax our assumptions of the fixed target area. The interaction of the key variables and the distance variables makes it possible to (easily) determine the range of the target area. The alternative specification checks whether our proposed target area is robust. Also, it checks for any nonlinear relationship of the external effects across space.

Second, we check the heterogeneity of the redevelopment external effects on property prices. There is a high variation in sizes of shopping centers. Large shopping centers are more inclined to have massive and distinguished redevelopment, such that the redevelopment of large shopping centers may have higher external effects compared with small shopping centers. To examine this, we separately estimate external effects for large and small shopping centers. We also test whether the external effects are heterogeneous between urban and rural areas. The convenience of shopping centers and solving the inconvenience (such as traffic congestion) may be valued differently by urban residents. The perception of external effects may differ for properties in urban areas. Furthermore, we also investigate if the redevelopment of indoor and outdoor shopping centers may generate different external effects on

⁷⁶The definition of our predefined target area is not equal to the catchment area of a shopping center. Catchment areas of shopping centers are – using our own experiences and anecdotal evidence – much larger than our target areas. This implies that we only measure local price effects of redevelopment on nearby housing markets.

property prices.

Third, we perform a repeat sales analysis to control for unobserved differences across properties and potential changes in the mix of residential properties that sell before and after the redevelopment of shopping centers. If there are relevant omitted property characteristics that are changed before or after the redevelopment of the shopping centers, there could be potential upward bias of the external effects in the hedonic analysis. Repeat sales methods only consider properties that are sold more than once during the observation period in the analysis. While this may yield a more selective sample compared to our proposed difference-in-difference hedonic analysis, it helps identifying whether unobserved property characteristics do play any role in our original estimates.

Finally, we focus on the definition of the control areas. Our proposed empirical methodology provides a simple way to determine the range of external effects of redevelopment across space, but identifying the “correct” control area is more controversial. Initially, we propose to use the outer ring – just outside the specified target area – as the control area. As an alternative, we propose to use the propensity score matching method to define control areas. For the difference-in-difference methodology, it is important that the target and control areas are identical, except for the event of redeveloping a shopping center. Matching estimators impute counterfactual observations by pairing properties in target areas with similar properties which are then defined as control areas.⁷⁷ The use of matching estimators is becoming more and more popular in the economic literature (e.g. McMillen & McDonald, 2002; Muehlenbachs et al., 2015; Ahlfeldt et al., 2017; Van Duijn et al., 2016; Koster & Van Ommeren, 2019). It should, however, be noted that changing the control area has limited effect on one of our key variables, $Target_i \times Post_t$, as variation over space and time of the shopping center redevelopment occurs within the target area.⁷⁸

⁷⁷More information on the techniques involved in matching estimators can be found in Abadie & Imbens (2006; 2011).

⁷⁸We thank an anonymous referee for this insightful comment.

5.4 Data

Our analysis combines data from multiple sources. First, we use residential property transactions in the Netherlands between 1990 and 2014 provided by the Dutch Association of Real Estate Agents (NVM), which covers around 70% of the total residential transactions in the Netherlands. Second, we use shopping center information provided by the Dutch Shopping Center Council (NRW). This data set contains detailed information of 989 shopping centers in the Netherlands that opened before 2011. Among these shopping centers, we observe 437 shopping centers which have been significantly redeveloped between 1979 and 2010.

From the shopping center data set, we selected the redeveloped shopping centers for further examination based on the following considerations. First, we excluded 13 shopping centers because they were redeveloped within 4 years after their opening.⁷⁹ These shopping centers are probably not redeveloped because of deterioration, which is different from the other redeveloped shopping centers and divergent from the focus of this paper. Then we selected shopping centers which have enough residential property transactions within the target and control areas. We exclude 116 shopping centers because we observe fewer than 30 property transactions either in the target (before and after redevelopment separately) or control area.⁸⁰ In addition, 14 shopping centers redeveloped before 1992 are excluded because for these shopping centers we do not have enough years of residential property transactions to measure trend effects before redevelopment. Furthermore, two shopping centers are excluded because they are located too close to the Dutch border, so that most of the target or control area around them is not located in the Netherlands. At last, we dropped 19 specialized shopping centers, including retail parks, factory outlet and theme-oriented centers, considering they have different purposes and thus may

⁷⁹Redevelopment involves various decision processes and costs, which means that the timing of redevelopment cannot be too close to the opening or last redevelopment of the shopping center. Therefore, we believe these 13 shopping centers that are divergent from the usual redevelopment cycle are redeveloped because of other reasons but not deterioration.

⁸⁰There are basically two situations why these shopping centers do not have enough property transactions around them. Most of these shopping centers are located in rural areas so that they do not have enough property transactions observed within 1,000 *m* of them, either before or after the redevelopment. There are also some dropped shopping centers that are situated near the edge of a relatively small residential area. Most of the property transactions happened in the target areas and thus we do not have enough property transactions in the control areas.

Table 5.1: Summary statistics of redeveloped shopping centers

	Mean	Std.Dev.	Median	Min	Max
Floor area (in 1,000 m^2)	9.342	11.021	5.7	2.5	90
Opening year	1976.015	10.666	1976	1885	2001
Renovation year	2000.458	4.622	2000	1992	2010
Number of outlets	35.703	34.785	24	3	257
Number of parking lots	332.238	557.980	200	0	6,400
Number of residential property transactions(<2,000 m)	3,146.462	2,206.889	2,717	202	13,132
Indoor (1 = yes)	0.447				
Park free (1 = yes)	0.722				
Number of observations	273				

Note: Our original dataset contains 989 shopping centers all over the Netherlands, of which there are 437 shopping centers that are redeveloped. 13 shopping centers are dropped out because the timing of the redevelopment is very close to the opening of the shopping center. We drop another 116 redeveloped shopping centers because there are not enough transactions in the target area (before or after redevelopment) or in the control area. Fourteen shopping centers redeveloped before 1992 are excluded because we observe too few observations to measure trend effects before redevelopment. Also, another two shopping centers are excluded because they are too close to the Dutch border so that most of the area around them within 2,000 m is not in the Netherlands. At last, we dropped 19 specialized shopping centers because they are built for different purposes compared with other traditional ones. This results in 273 redeveloped shopping in our analysis.

cause different influences on nearby residential properties compared with other traditional shopping centers.⁸¹ This results in 273 redeveloped shopping centers used in our analysis. Figure 5.1 presents the location of all redeveloped shopping centers in our dataset. The triangles represent redeveloped shopping centers used in our analysis, while the crosses are those shopping centers which we dropped.

Table 5.1 presents the summary statistics of the redeveloped shopping centers used in our analysis. As shown, our sample covers both relatively small shopping centers (2,500 m^2) and large ones (90,000 m^2). The average size of these shopping centers is 93,420 m^2 . There are shopping centers in the dataset which initially opened about 100 years ago, but there are also some newly built ones that are opened after

⁸¹According to the European Shopping Center Standard published by International Council of Shopping Centers (ICSC), shopping centers are grouped into two categories: traditional and specialized. Specialized shopping centers represent the ones built for a specific purpose, including retail parks, factory outlet centers and theme-oriented centers. A traditional shopping center is the one with all purposes. For more detailed information, see <https://www.icsc.org/uploads/research/general/euro-standard-only.pdf>.

Figure 5.1: Location of redeveloped shopping centers

Note: The triangles are those shopping centers used in our analysis, while the crosses represent those ones that are redeveloped but dropped out from our analysis.

2000. All these shopping centers are redeveloped between 1992 and 2010, with a median redevelopment year of 2000. The average number of property transactions within 2,000 *m* of a redeveloped shopping center is 3,146. About 44.7% of these redeveloped shopping centers are enclosed (rather than open-air) and about 72.2% of them provide free parking.

The NVM data contain detailed information on the transactions of residential properties, including residential property price, exact street address, type of property, floor space, year built, number of rooms and so on. We select those properties

Table 5.2: Summary statistics of residential property transactions

	Mean	Std. Dev.	Median	Min	Max
Structural characteristics					
Residential property price (in 1,000 euros)	185.810	101.804	165.630	25.185	1,200
Size (m^2)	114.381	35.465	112	45	260
Price per m^2	1,638.973	682.405	1,600	253.460	4,666.667
Number of rooms	4.279	1.230	4	1	10
Distance to the nearest redeveloped shopping center (in m)	888.485	515.509	825.501	0	2,000
Apartment (1 = yes)	0.297				
Property type - Town (1 = yes)	0.366				
Property type - Corner (1 = yes)	0.146				
Property type - Semi-detached (1 = yes)	0.124				
Property type - Detached (1 = yes)	0.067				
Balcony (1 = yes)	0.270				
Terrace (1 = yes)	0.057				
Parking (1 = yes)	0.278				
Well-maintained garden (1 = yes)	0.260				
Bad inside maintenance (1 = yes)	0.017				
Bad outside maintenance (1 = yes)	0.011				
Central heating (1 = yes)	0.904				
Monument (1 = yes)	0.004				
Building periods					
<1945 (1 = yes)	0.226				
1945-1960 (1 = yes)	0.066				
1961-1970 (1 = yes)	0.180				
1971-1980 (1 = yes)	0.188				
1981-1990 (1 = yes)	0.157				
1991-2000 (1 = yes)	0.123				
>2000 (1 = yes)	0.061				
Number of observations	828,567				

Note: In our sample, we only include residential properties that are located within 2,000 m of the redeveloped shopping centers and were sold between 1990 and 2014. Observations whose property price per square meter is smaller than 1st percentile or larger than 99th percentile (based on each year) are deleted. Furthermore, we dropped observations whose size is outside of the 1st and 99th percentiles.

that are located within 2,000 m of each redeveloped shopping center. We exclude properties whose transaction price per m^2 is beyond the 1st and 99th percentiles in each transaction year. Besides, we also omit properties whose size is smaller than the 1st percentile or larger than 99th percentile of all the properties. Finally, there are 828,567 residential property transactions left in our sample.

Table 5.2 shows summary statistics of the residential property transactions. The

transaction prices range from 25,185 to 1,200,000 euros, with an average of 185,810 euros. The average lot size of transacted properties is about 114 m^2 . The lowest transaction price per m^2 is about 253 euros; this is because some property transactions in our dataset occurred in the early 1990s and in rural areas. On the contrary, the highest price per m^2 which is about 4,667 euros reflects those properties located in central cities, such as Amsterdam. The average distance of each property to its nearest redeveloped shopping center is about 888 meters, with a median around 826 meters. Only a few properties in our dataset are built after 2000 which is not surprising as newly built properties are often not recorded by the NVM and most redeveloped shopping centers in our sample are originally located within existing residential areas.

Table 5.3 depicts the summary statistics of residential property transactions in our initially chosen target and control areas separately. There are more observations in the target area, and this is because usually the target area is located closer to the neighborhood center. The average residential property price and price per m^2 in the target area are smaller than those in the control area but the difference is not even a quarter of a standard deviation. If differences in property prices are mainly caused by the location of the property, it can be captured by small-scale location fixed effects.

One of the assumptions of the difference-in-difference methodology is that the development of the dependent variable – in our case, residential property prices – is identical between the target and control area before redevelopment. Because we observe many redeveloped shopping centers with different redevelopment timings, it is not easy to test this assumption. In Appendix 5.C, we show figures of the development of average residential property prices and average residential property prices per m^2 of target and control areas before and after redevelopment. The trend in both target and control areas follow similar patterns, which gives us initial assurance that the difference-in-difference assumption is satisfied. To probe more deeply into our unconfoundedness assumption, in our sensitivity analysis we also consider different definitions of the control area using propensity score matching.

Table 5.3: Summary statistics of residential property transactions by target and control area

	Target area (0-1,000 <i>m</i>)					Control area (1,000-2,000 <i>m</i>)				
	Mean	Std. Dev.	Median	Min	Max	Mean	Std. Dev.	Median	Min	Max
Structural characteristics										
Residential property price (in 1,000 euros)	178.102	96.327	160	25.185	1170	197.637	108.621	175	25.185	1200
Size in <i>m</i> ²	112.228	34.577	110	45	260	117.685	36.541	115	45	260
Price per <i>m</i> ²	1,604.993	658.861	1,570.777	253.460	4,649.123	1,691.118	713.896	1,652	252.481	4,650.538
Number of rooms	4.238	1.229	4	1	10	4.343	1.228	4	1	10
Distance to the nearest redeveloped shopping center (in <i>m</i>)	534.521	264.569	537.705	0	999.996	1431.675	280.758	1,406.570	1,000.003	2,000
Apartment (1 = yes)	0.318					0.264				
Property type - Town (1 = yes)	0.369					0.361				
Property type - Corner (1 = yes)	0.148					0.144				
Property type - Semi-detached (1 = yes)	0.108					0.149				
Property type - Detached (1 = yes)	0.057					0.082				
Balcony (1 = yes)	0.285					0.247				
Terrace (1 = yes)	0.053					0.062				
Parking (1 = yes)	0.261					0.303				
Well-maintained garden (1 = yes)	0.243					0.286				
Bad inside maintenance (1 = yes)	0.017					0.017				
Bad outside maintenance (1 = yes)	0.011					0.011				
Central heating (1 = yes)	0.906					0.901				
Monument (1 = yes)	0.003					0.005				
Building periods										
<1945	0.204					0.259				
1945-1960	0.062					0.072				
1961-1970	0.221					0.117				
1971-1980	0.210					0.153				
1981-1990	0.163					0.148				
1991-2000	0.091					0.173				
>2000	0.049					0.079				
Number of observations	501,663					326,904				

5.5 Main results

In this section, we report the regression results of the difference-in-difference hedonic price model. We investigate whether there are external effects of redeveloping shopping centers on nearby residential property prices and what the magnitudes of these external effects are across space and over time. We start by reporting the results of our preferred model following Equation (5.1). Initially the target area is within 1,000 *m* to the nearest redeveloped shopping center, while the control area is between 1,000 and 2,000 *m*. Table 5.4 reports the key coefficients and standard errors of various specifications where we consider 273 redeveloped shopping centers.⁸²

Column (1) reports the results from a naive specification which only includes the key variables and their interactions, year of sale fixed effects and location fixed effects at the postcode (PC6) level.⁸³ The small-scale location fixed effects control for all time-invariant location characteristics. As shown in column (1), the coefficient on $Target_i$ is negative and significant, suggesting that properties located just next to a redeveloped shopping center and sold just before the redevelopment ($Distance_i = 0$ and $Trend_t = 0$) sell for 11.8% ($= (\exp^{(-0.126)} - 1) \times 100$) less on average than properties located in the control area. This seems to suggest that just before redevelopment, shopping centers may be so outdated that they are a blister to nearby residential properties, although this effect may not be causal. The coefficient of $Target_i \times Distance_i$ is positive and significant, which means the price difference becomes smaller for properties located further from a redeveloped shopping center. The price difference disappears – on average – for properties located around 900 to 1,000 *m* from a shopping center. This supports our proposed radius of the target area. The coefficient of $Target_i \times Trend_t$ measures how the price difference before redevelopment between the target and control area varies over time. Its coefficient is negative and significant. This implies that, on average, price difference becomes greater over time – more than a quarter of a percent per year – until the moment of redevelopment. When it comes closer to the redevelopment, the price

⁸²We use clustered standard errors at redeveloped shopping center level to control for spatial correlation. We also experimented with using standard errors clustered at neighborhood or postcode level. The results are really similar, and our main conclusion remains unchanged.

⁸³In the Netherlands, a postcode (PC6) is a combination of four digits and two letters. One PC6 represents a street (on average, 15 properties).

Table 5.4: Difference-in-difference regression results

	(1)	(2)	(3)	(4)
Sample	<2,000 <i>m</i>	<2,000 <i>m</i>	<2,000 <i>m</i>	<2,000 <i>m</i>
Target area	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>
Control area	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>
Target	-0.126*** (0.0280)	-0.0300* (0.0174)	-0.0247 (0.0187)	-0.00693 (0.00837)
Target×Distance	0.000123*** (2.73e-05)	2.79e-05 (1.74e-05)	2.26e-05 (1.87e-05)	6.60e-06 (9.12e-06)
Target×Trend	-0.00315** (0.00149)	-0.00275* (0.00146)	-0.00255* (0.00131)	-0.000862 (0.00149)
Target×Trend×Distance	2.81e-06* (1.59e-06)	2.52e-06 (1.58e-06)	2.29e-06 (1.50e-06)	7.18e-07 (1.77e-06)
Target×Post	0.0123** (0.00609)	0.0136** (0.00560)	0.0142*** (0.00548)	0.0113* (0.00633)
Target×Post×Distance	-8.14e-06 (7.54e-06)	-1.09e-05* (6.52e-06)	-1.18e-05* (6.70e-06)	-7.57e-06 (7.85e-06)
Target×Post×Trend	-0.00458*** (0.000917)	-0.00396*** (0.000863)	-0.00347*** (0.000793)	-0.00161** (0.000699)
Target×Post×Trend×Distance	4.65e-06*** (9.18e-07)	3.89e-06*** (8.53e-07)	3.59e-06*** (8.49e-07)	1.75e-06** (8.36e-07)
Year fixed effects (24)	Yes	Yes	Yes	Yes
Structural characteristics (14)	No	Yes	Yes	Yes
Building periods (6)	No	Yes	Yes	Yes
Shopping center characteristics (6)	No	No	Yes	Yes
Shopping center type fixed effects (8)	No	No	Yes	Yes
Neighborhood characteristics (5)	No	No	Yes	Yes
PC6 fixed effects (91,502)	Yes	Yes	Yes	No
PC4 fixed effects (1,281)	No	No	No	Yes
Observations	828,567	828,567	828,567	828,567
Adjusted R^2	0.882	0.941	0.942	0.901

Note: Dependent variable is the log of residential property prices. We include 273 redeveloped shopping centers in our analysis. Standard errors clustered at redeveloped shopping center level and in parentheses. The other coefficients can be obtained from the authors.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

difference between the target and control area becomes broader. The positive coefficient of $Target_i \times Trend_t \times Distance_i$ shows that the trend effect before redevelopment changes with distance. For properties that are further away from a redeveloped shopping center, the price difference before redevelopment grows more slowly over time.

The coefficient on $Target_i \times Post_t$ captures the positive external effects of redevelopment for residential properties located just next to a redeveloped shopping center and sold just after the redevelopment ($Distance_i = 0$ and $Trend_t = 0$). The results in column (1) show that the redevelopment generates on average 1.23% increase in residential property prices when comparing those properties with properties in the

control area. The positive coefficient decreases with distance, as suggested by the negative coefficient before $Target_i \times Post_t \times Distance_i$. However, this coefficient is not statistically significant. The negative coefficient of $Target_i \times Post_t \times Trend_t$ indicates the external effects of redevelopment on property prices decrease over time. These results are in line with our expectations formulated in Section 2. The coefficient of $Target_i \times Post_t \times Trend_t \times Distance_i$ shows that positive external effects after redevelopment diminishes more quickly over time for properties that are closer to the shopping center.

In Column (2), we control for many property characteristics which are standard in hedonic price studies. As expected, coefficients of our key variables are sensitive when property characteristics are omitted. It is noteworthy that the price difference between properties in the target and control area becomes much smaller. For properties located next to a redeveloped shopping center and sold just before the redevelopment, the transaction price is about 3% lower compared with properties in the control area. Both interaction terms with distance become statistically insignificant, although they still have the expected sign. This means the price difference before redevelopment is indifferent to distance. Properties located closer to a redeveloped shopping center are not sold for less before redevelopment. The external effect of redevelopment increases to 1.37% for properties located next to a redeveloped shopping center and sold just after the redevelopment. Different from column (1), the coefficient of $Target_i \times Post_t \times Distance_i$ is significant now, which means a property experiences larger external effects of the redevelopment if it is located closer to the shopping center.

Next, we include shopping center characteristics and neighborhood characteristics in column (3). The neighborhood characteristics are time-varying location variables that may have an influence on property prices. For the price difference between the target and control area before redevelopment, only the coefficient before $Target_i \times Trend_t$ remains significant at 10% level. This means there is no price difference between the target and control area just before redevelopment ($Trend_t = 0$). For external effects after redevelopment, the results are quite similar as previous estimates. For properties that are next to a redeveloped shopping center and sold just after redevelopment, the redevelopment increases their prices by about 1.43%,

Figure 5.2: Change of the average external effects on property prices after redevelopment

Note: T represents the redevelopment year of a shopping center. $T + l$ indicates l years after the redevelopment. The figure shows the change of external effects over space if properties are transacted at four different years after the redevelopment of shopping centers. The figures are calculated based on the results of column (3) of Table 5.4.

compared with properties that are not affected by the redevelopment of shopping centers. The other interaction terms also have intended signal and are significant, just as column (2).

Since column (3) is our complete and preferred specification of regression, we draw graphs using results from column (3) to illustrate in more detail about the spatial and temporal variations of the external effects after redevelopment. Figure 5.2 shows the dynamics of the positive external effect in space and time after redevelopment. The graph indicates that the positive external effects decrease over space and get close to zero around 1,000 m .⁸⁴ This implies that positive external effects on residential housing markets are, on average, rather local. Figure 5.2 also shows the positive external effects decline over time. The external effects decrease faster for properties closer to the redeveloped shopping center. Although in the 4th year after redevelopment the external effects remain positive, their values are relatively

⁸⁴Figure 5.2 clearly shows that our proposed target area of a 1,000 m from shopping centers is reasonable and that no external effects seem to exist in areas further than 1,000 m of shopping centers.

Figure 5.3: Another way to look at the change of the average external effects on property prices after redevelopment

Note: T represents the redevelopment year of a shopping center. The figure shows the change of external effects over time for five different areas depending on the distance to the shopping center (in *m*). The figures are calculated based on the results of Column (3) of Table 5.4.

small. Figure 5.2 suggests that the external effects are rather local and wear off rather quickly across space and over time.⁸⁵

The dynamic pattern of the external effects of shopping center redevelopment is best revealed in Figure 5.3. We see that the positive external effects decrease rather quickly over time. The positive external effects become almost zero in the 4th year after redevelopment, for all properties with different distances. This again implies that redevelopment of shopping centers has a substantial impact on nearby residential housing markets just after redevelopment, but that shopping centers deteriorate – in the broadest sense of the word – rather quickly. The results in Table 5.4, which are supported by graphs in Figure 5.2 and 5.3, are consistent with our theoretical framework on the redevelopment external effects of shopping centers in Section 5.2.

From column (1) to (3), we use PC6 to control for unobserved time-invariant location characteristics. However, it is argued that PC6 can be too small-scaled and restrictive so that it may absorb part of the treatment effect (Abbott & Klaiber, 2011).

⁸⁵In Appendix 5.D, we draw the external effects with their confidence intervals from the 1st year to the 4th year after redevelopment separately.

As a result, we replace PC6 with PC4 in column (4) of Table 5.4. The insignificance of the first four coefficients shows that there is no price difference at all between the target and control area before redevelopment. The redevelopment increases the price by about 1.14% for properties located next to the redeveloped shopping center and sold just after the redevelopment, which is smaller compared with results using PC6. This external effect decreases over time and it decreases faster for properties located closer to the redeveloped shopping center. Our main conclusion remains the same.

5.6 Sensitivity analyses

In this section, we provide additional analyses to check the robustness of our regression results. First, we use an alternative specification of our preferred model to relax our assumptions of the fixed target area range. It also checks whether our proposed target area is reasonable and if the external effects across space are indeed as linear as suggested by our main results. Second, we test the heterogeneity of the external effects of redevelopment. Third, we perform a repeat sales analysis to control for unobserved differences across properties and potential changes in the mix of properties that sell before and after the redevelopment of shopping centers. Last, we focus on defining different control areas by using the propensity score matching method.

5.6.1 Target area

In our preferred model, we set our sample to be within 2,000 *m* of a redeveloped shopping center. The target area is within 1,000 *m* of a redeveloped shopping center, while the control area is between 1,000 *m* and 2,000 *m*. Using the specifications in Table 5.4 we tested the functional form of the distance decay of the external effects. The results indicate that the distance decay of the external effects shows most similarities with a linear functional form. However, the range of target area and the distance decay of the external effects may be different before and after the redevelopment. We propose to estimate a different specification to check the external effects of the redevelopment of shopping centers by relaxing the assumptions on linearity. To allow for different target ranges and nonlinear distance decay, we divide the sample area

into different rings with a bandwidth of 250 m . Instead of using a continuous distance variable, we use dummy variables which indicate whether a property is within a distance range of a redeveloped shopping center. In other words, we create a set of dummy variables which represent 250 m rings (0-250, 250-500, 500-750 and 750-1,000) around a redeveloped shopping center and observe the average target effect of properties located within the same distance ring. We can combine the ring variables with the difference-in-difference method and generate this alternative specification of our preferred model. The alternative specification is as follows:

$$\begin{aligned} \log(P_{ijt}) = & \alpha + \omega_{1z}R_zTarget_i + \omega_{2z}R_zTarget_i \times Trend_t + \omega_{3z}R_zTarget_i \times Post_t \\ & + \omega_{4z}R_zTarget_i \times Post_t \times Trend_t + \phi X_{it} + \gamma_t + \mu_j + \varepsilon_{it}, \end{aligned} \quad (5.2)$$

where R_z is a set of dummy variables for each 250 m ring. It equals one if a property is located within the corresponding 250 m ring z . We include the interaction terms of the ring dummy variables and key difference-in-difference variables. Like our preferred model in Table 5.4, we also include structural characteristics of properties, shopping centers and neighborhoods, year fixed effects, and location fixed effects as control variables. Therefore, the coefficients measure the heterogeneity of the average external effects for each distance ring. Moreover, it provides a sensitivity check on whether we correctly defined the predefined target area.

Table 5.5 shows the regression results of Equation (5.2). Column (1) excludes redeveloped shopping center characteristics and neighborhood characteristics, while column (2) includes them. The results of these two columns are quite similar. Both columns show that, for a property in the target area of a redeveloped shopping center and sold just before the redevelopment, its price is not significantly different with a similar property in the control area. Only properties located between 250 and 500 m of a redeveloped shopping center have a decreasing trend of price. It could well be that this drives our negative trend decay coefficient which is presented in Table 5.4.

The positive coefficients on our second key variable, $R_zTarget_i \times Post_t$, show a linear distance decay effect in line with the results in Table 5.4. For a property within 250 m of a redeveloped shopping center and sold just after the redevelopment, its price increases by about 1.25%. The effect decreases to 0.95% at 250-500 m . The ex-

Table 5.5: Results of the alternative specification

Sample	(1)	(2)
	<2,000 <i>m</i>	<2,000 <i>m</i>
Target area	0-1,000 <i>m</i>	0-1,000 <i>m</i>
Control area	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>
Target (0-250 <i>m</i>)	-0.00898 (0.00867)	-0.00752 (0.00894)
Target (250-500 <i>m</i>)	-0.00924 (0.00761)	-0.00847 (0.00747)
Target (500-750 <i>m</i>)	-0.00898 (0.00669)	-0.00864 (0.00656)
Target (750-1000 <i>m</i>)	-0.00172 (0.00588)	-0.00135 (0.00565)
Target×Trend (0-250 <i>m</i>)	-0.00134 (0.00138)	-0.00127 (0.00124)
Target×Trend (250-500 <i>m</i>)	-0.00243** (0.00110)	-0.00225** (0.000966)
Target×Trend (500-750 <i>m</i>)	-0.00154 (0.00111)	-0.00144 (0.000983)
Target×Trend (750-1,000 <i>m</i>)	-4.07e-05 (0.00104)	-9.36e-05 (0.000951)
Target×Post (0-250 <i>m</i>)	0.0125** (0.00573)	0.0124** (0.00557)
Target×Post (250-500 <i>m</i>)	0.00872* (0.00501)	0.00943* (0.00488)
Target×Post (500-750 <i>m</i>)	0.00685 (0.00503)	0.00694 (0.00508)
Target×Post (750-1,000 <i>m</i>)	0.00463 (0.00578)	0.00424 (0.00573)
Target×Post×Trend (0-250 <i>m</i>)	-0.00332*** (0.000772)	-0.00290*** (0.000745)
Target×Post×Trend (250-500 <i>m</i>)	-0.00261*** (0.000717)	-0.00226*** (0.000626)
Target×Post×Trend (500-750 <i>m</i>)	-0.00138* (0.000719)	-0.00100 (0.000663)
Target×Post×Trend (750-1,000 <i>m</i>)	-0.000672 (0.000615)	-0.000480 (0.000588)
Year fixed effects (24)	Yes	Yes
Structural characteristics (14)	Yes	Yes
Building periods (6)	Yes	Yes
Shopping center characteristics (6)	No	Yes
Shopping center type fixed effects (8)	No	Yes
Neighborhood characteristics (5)	No	Yes
PC6 fixed effects (91,502)	Yes	Yes
Observations	828,567	828,567
Adjusted R^2	0.941	0.942

Note: Dependent variable is the log of residential property prices. Standard errors clustered at redeveloped shopping center level and in parentheses. The other coefficients can be obtained from the authors.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

ternal effects decrease gradually over time and they decrease faster for properties within 250 *m* of a redeveloped shopping center than those at 250-500 *m*, as indicated

by the negative and significant coefficients before $R_zTarget_i \times Post_t \times Trend_t$. Most coefficients of the 500-750 and 750-1,000 m ring dummy variables are insignificant, which means properties in these rings are on average not affected by the external effects of shopping centers redevelopment. This suggests a smaller target area compared with our results in Table 5.4 and that we can reduce the radius of our target area to 500 m . We ran our baseline regressions again with target areas that are within 500 m of a redeveloped shopping center and control areas unchanged. The results are quite similar.

5.6.2 Heterogeneity

Our analysis above discusses the average external effect of redevelopment of shopping centers on property prices. However, there may exist heterogeneity in the external effects of redeveloped shopping centers. It is notable that there is a high variation in sizes of redeveloped shopping centers, ranging from 2,500 to 90,000 m^2 . It is likely that larger redeveloped shopping centers will generate higher external effects on nearby property prices. This is because large shopping centers usually have broader catchment areas and their redevelopment can attract more attention from media and residents. Besides, the redevelopment of a large shopping center is more possible to have road restructured so that traffic congestion can be alleviated or even completely solved. We also investigate whether the redevelopment of shopping centers is heterogeneous for properties in the urban and rural areas. Property prices in urban and rural areas are heterogeneous (DiPasquale & Wheaton, 1996). Residents who choose to live in urban areas may value shopping centers differently from those in rural areas. Therefore, the perception of the external effects of redevelopment might differ between properties in urban and rural areas. In the end, we check the heterogeneity in external effects of redevelopment between indoor and outdoor shopping centers.

Table 5.6 reports our results of heterogeneity tests. First, column (1) to (2) show estimations for small and large shopping centers separately.⁸⁶ For properties next to small shopping centers, they are sold on average 3.1% less just before redevelopment, compared to similar properties in the control area. The price difference shrinks

⁸⁶We followed ICSC's standard to identify shopping centers with fewer than 19,999 m^2 as small; the others as large. Most of our shopping centers are small shopping centers.

gradually with distance but broadens over time. However, there is no price difference at all between the target and control area around large shopping centers. The coefficients before $Target_i \times Post_t$ in column (1) and (2) show that the redevelopment of large shopping centers generate higher positive effects (2.47%) on nearby property prices than small shopping centers (1.35%), just as expected. The redevelopment external effects of both types of shopping centers show similar patterns in their changes over time, but clearly the effect of large shopping centers diminishes at a faster pace. Small shopping centers also have a negative and significant coefficient of $Target_i \times Post_t \times Distance_i$, which means the positive external effects of small shopping centers decrease with distance; however, this coefficient is not significant for large shopping centers.

Second, in column (3) and (4), we show regression results for properties in urban and rural areas separately.⁸⁷ For urban areas, there is no price difference between target and control area for properties sold just before the redevelopment. For properties in urban areas located next to the redevelopment shopping centers and sold just after the redevelopment, their prices increase by 1.44%, which is almost the same as our baseline results. The positive external effects caused by redevelopment decrease over time and space. However, the rural areas show quite different patterns. For rural area, the properties located next to the redeveloped shopping center sell on average 6.42% less than those in the control area just before redevelopment. The redevelopment of shopping centers has no external effects at all on property prices. This suggests residents living in rural areas may indeed have a different preference over shopping centers and may not be willing to pay higher prices for properties near a redeveloped shopping center. From a policy point of view, this implies to redevelop a shopping center in the urban area may bring more social benefits. This suggests residents living in rural areas may indeed have a different preference over shopping centers and may not be willing to pay higher prices for properties near a redeveloped shopping center. From a policy point of view, this implies to redevelop a shopping center in the urban area may bring more social benefits.

⁸⁷Statistics Netherlands provides information about the urbanity level of each neighborhood from 1992 to 2010. Each neighborhood is given an urbanity class 1-5 based on its density of addresses. Class 1 represents very high urbanity, which represents more than 2500 addresses per km^2 . Class 5 represents no urbanity, which represents less than 500 addresses per km^2 . We define the first two classes as urban areas and the others as rural areas.

Table 5.6: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Small	Large	Urban	Rural	Indoor	Outdoor
Sample	<2,000 <i>m</i>	<2,000 <i>m</i>	<2,000 <i>m</i>	<2,000 <i>m</i>	<2,000 <i>m</i>	<2,000 <i>m</i>
Target area	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>
Control area	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>	1,000-2,000 <i>m</i>
Target	-0.0302* (0.0179)	0.00744 (0.0843)	0.00464 (0.0252)	-0.0622** (0.0246)	-0.0269 (0.0270)	-0.0187 (0.0249)
Target×Distance	3.14e-05* (1.76e-05)	-2.28e-05 (8.30e-05)	6.05e-06 (2.49e-05)	4.95e-05* (2.63e-05)	2.54e-05 (2.76e-05)	1.56e-05 (2.44e-05)
Target×Trend	-0.00243* (0.00139)	-0.00510 (0.00360)	-0.00341* (0.00176)	-0.00311* (0.00181)	-0.00405** (0.00166)	-0.00111 (0.00191)
Target×Trend×Distance	2.57e-06 (1.57e-06)	3.64e-06 (4.02e-06)	3.23e-06* (1.94e-06)	1.90e-06 (2.46e-06)	3.86e-06* (1.98e-06)	8.55e-07 (2.18e-06)
Target×Post	0.0134** (0.00587)	0.0244* (0.0140)	0.0143** (0.00719)	0.00913 (0.00917)	0.00662 (0.00762)	0.0186** (0.00752)
Target×Post×Distance	-1.24e-05* (7.22e-06)	-2.31e-05 (1.57e-05)	-1.73e-05* (9.53e-06)	1.66e-06 (1.30e-05)	1.79e-06 (1.07e-05)	-2.00e-05** (7.89e-06)
Target×Post×Trend	-0.00315*** (0.000829)	-0.00588*** (0.00199)	-0.00502*** (0.00106)	-0.00153 (0.00122)	-0.00302** (0.00117)	-0.00406*** (0.00105)
Target×Post×Trend×Distance	3.08e-06*** (8.49e-07)	7.76e-06** (3.37e-06)	4.48e-06*** (1.16e-06)	1.54e-06 (1.33e-06)	2.20e-06* (1.32e-06)	4.83e-06*** (1.09e-06)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Structural characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Building periods	Yes	Yes	Yes	Yes	Yes	Yes
Shopping center characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Shopping center type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood characteristics	Yes	Yes	Yes	Yes	Yes	Yes
PC6 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	734,345	94,222	503,633	324,934	371,929	456,638
Adjusted R^2	0.942	0.944	0.939	0.950	0.942	0.943

Note: Dependent variable is the log of residential property prices. Standard errors clustered at redeveloped shopping center level and in parentheses. The other coefficients can be obtained from the authors.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Third, another potential issue is that the redevelopment of indoor and outdoor shopping centers may generate different external effects on nearby property prices. This is because, for indoor shopping centers, all shopping activities happen within the enclosed “big box” and they are expected to have little influence on nearby property prices. For example, indoor shopping centers do not make noises as serious as outdoor shopping centers, so the redevelopment of indoor shopping centers may not have as high external effects as outdoor shopping centers. Column (5) and (6) of Table 5.6 report the results for indoor and outdoor shopping centers separately. For both types of shopping centers, there is almost no price difference between target and control area before redevelopment. The redevelopment of outdoor shopping centers increases the price of properties by about 1.88% on average, for properties located next to a redeveloped shopping center and sold just after the redevelopment. The positive external effects decrease over time and space. On the contrary, the redevelopment of indoor shopping centers shows no external effects immediately, as indicated by the insignificant coefficient of $Target_i \times Post_t$. However, the negative coefficient before $Target_i \times Post_t \times Trend_t$ indicates the redevelopment of indoor shopping centers may decrease nearby property price gradually over time.

5.6.3 Repeat sales analysis

Our main results are based on the difference-in-difference hedonic price model. It is well-known that hedonic price models are sensitive to omitted variables and failing to include important variables that influence property prices may cause biased coefficients. In our case, possible omitted variables are mainly unobserved property and neighborhood characteristics. In our data set we observe properties that are sold multiple times between 1990 and 2014. This enables us to use a repeat sales analysis to check the robustness of the results from our difference-in-difference hedonic price model. A repeat sales analysis controls for all time-invariant characteristics of properties and neighborhoods that may influence the property prices.⁸⁸ Following the

⁸⁸The repeat sales method has three shortcomings. First, it does not control for time-variant variables which may influence property prices. This may still lead to biased results. Second, there may exist a selection bias because it only includes property that are sold more than once. Third, repeat sales analysis always decreases the number of observations used in the analysis, which can lead to a less trustworthy estimation results.

repeat sales specifications used by Schwartz et al. (2006) and Van Duijn et al. (2016), we derive our repeat sales equation as follows:

$$\begin{aligned}\Delta_{t,s} \log(P_{ij}) = & \alpha \textit{Before-Post}_i + \beta \textit{Before-Post}_i \times \textit{Distance}_i + \theta \textit{Target}_i \times \textit{Post}_t \\ & \times \textit{Trend}_t + \delta \textit{Target}_i \times \textit{Post}_t \times \textit{Distance}_i \times \textit{Trend}_t + \phi \Delta_{t,s} X_i \\ & + \Delta_{t,s} \gamma + \Delta_{t,s} \varepsilon_{ij},\end{aligned}\tag{5.3}$$

where $\Delta_{t,s}$ represents the difference between two sales and $\textit{Before-Post}_i$ is a dummy variable indicating whether these two sales of a property in the target area happened before and after redevelopment separately.⁸⁹ $\textit{Before-Post}_i$ measures how the property price is going to change due to redevelopment if a property was sold before redevelopment and it was sold again after redevelopment. Similar as our preferred model, $\textit{Before-Post}_i$ is interacted with the distance variable to investigate how the effect is going to change with distance. All time-invariant variables are eliminated from Equation (5.3).

Table 5.7 reports the regression results of the repeat sales analysis. For a property that is located next to a redeveloped shopping center ($\textit{Distance}_i = 0$) and sold twice (once before the redevelopment and once after the redevelopment), the impact of the redevelopment on residential property prices is 1.9%. This suggests the redevelopment of shopping centers has a positive external effect on nearby property prices. Compared to Table 5.4, the repeat sales analysis reports estimates with similar signs and magnitudes. These results suggest that there is little reason to be concerned about unobserved time-invariant differences of properties in the hedonic regressions discussed in Section 5.3.

5.6.4 Propensity score matching

For the difference-in-difference methodology it is important that the target and control area are comparable, especially if one wants to interpret the coefficient of the $\textit{Target}_i$ variable. This means, in our case, properties in the target and control area

⁸⁹For a property located in the target area, $\textit{Before-Post}_i = 1$ if this property was sold before the redevelopment and it was sold again after the redevelopment.

Table 5.7: Results of repeat sales analysis

	(1)
Sample	<2,000 <i>m</i>
Target area	0-1,000 <i>m</i>
Control area	1,000-2,000 <i>m</i>
Transition: Before-Post	0.0188*** (0.00713)
Before-Post × Distance	1.75e-05** (7.68e-06)
Target × Post × Trend	-0.00165*** (0.000538)
Target × Post × Trend × Distance	2.61e-06*** (7.52e-07)
Differenced year dummies	Yes
Differenced structural characteristics	Yes
Differenced neighborhood characteristics	Yes
Building periods	No
Shopping center characteristics	No
Shopping center type fixed effects	No
PC6 fixed effects	No
Observations	233,710
Adjusted R^2	0.688

Note: Dependent variable is the difference between the log of residential property prices of the same residential property sold at different times. Standard errors clustered at redeveloped shopping center level and in parentheses. Building periods, shopping center characteristics, shopping center type and PC6 fixed effects are time-invariant and therefore not estimated in this analysis. The other coefficients can be obtained from the authors.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

should be identical, except that one is within 1,000 *m* of a redeveloped shopping center and the other is not. In Appendix 5.C, we show that the trend of residential property prices in target and control areas follow similar patterns both before and after redevelopment. This gives us initial assurance that the difference-in-difference assumption is satisfied. We observe 273 redeveloped shopping centers with each a different timing of redevelopment. One could argue that the trend of residential property prices does not reflect the assumption of identical patterns between the predefined target and control areas.

Table 5.8: Comparison of neighborhood characteristics based on propensity score matching

	Target area		Control area	
	Mean	Std. Dev.	Mean	Std. Dev.
Average household size	2.176	0.776	2.160	0.795
Population density per km^2	4,280.884	3,951.096	4,261.920	4,249.824
Number of residents	2,356.248	2,741.534	2,258.966	2,595.133
Young people (<25 years) (%)	25.430	11.060	25.269	11.323
Elderly people (>65 years) (%)	13.827	11.325	13.429	10.753
Immigrants(%)	11.366	14.512	11.756	15.117
Neighborhood size (in hectare)	133.168	321.703	135.509	559.035
Average income per resident (in 1,000 euros)	2.199	4.799	2.089	4.776
Number of neighborhoods	3,164		3,164	

Note: The target area refers to neighborhoods within 1,000 m of a redeveloped shopping center. The control area refers to matched neighborhoods based on propensity score matching and located between 1,500-10,000 m of a redeveloped shopping center.

Another potential issue for our analysis is selection. In Section 5.4, we show that before redevelopment there exists a price difference between properties in the target and control areas. Except that this is affected by the redevelopment project, it is also possible there is some form of selection bias that the decision of redevelopment is dependent on the state of the neighborhood. Shopping centers in declining neighborhoods are targeted for redevelopment, so that they can revitalize the neighborhood. Another possibility is the location decision of developing shopping centers is historically determined by shopping center owners and policy makers, targeting at less attractive neighborhoods, because land costs are lower for owners therefore risk is lower and policy makers believe shopping centers make neighborhoods more attractive. In these cases, the target area is not assigned randomly and there can be a selection bias.

To solve for these concerns, we propose to use the propensity score matching method to match each target area to a similar control area. We calculate a propensity score for each neighborhood before the redevelopment based on a probit regression. We include many neighborhood characteristics in the probit regression, such as population density, average household size, average income per resident, percentage of immigrants and so on.

Table 5.8 shows the summary descriptive statistics of the neighborhood charac-

teristics included in the probit regression. If two neighborhoods before the redevelopment have similar propensity scores, they are assumed to be identical to each other and have similar characteristics. We can find a matched control neighborhood for each target neighborhood by minimizing the difference in propensity scores. To ensure residential property prices in control neighborhoods are not affected by redeveloped shopping centers, we restrict all potential matched control neighborhoods to be located between 1,500 *m* and 10,000 *m* from the redeveloped shopping centers. Our target area remains within 1,000 *m* of the redeveloped shopping centers.

Table 5.9 presents the regression results based on Equation (5.1). The only difference compared to the results in Table 5.4, our main results, is that our predefined target areas are now compared to residential properties in control areas defined by a propensity score matching method. Similar to Table 5.4, column (1) includes only our key difference-in-difference variables, year fixed effects and location fixed effects. Column (2) adds property characteristics and Column (3) adds shopping center and neighborhood characteristics. Column (3) is the focus of our analysis. Compared with column (3) of Table 5.4, the difference is that the coefficient before $Target_i$ becomes positive but still insignificant. A property sold just before redevelopment and just next to the shopping center ($Distance_i = 0$ and $Trend_t = 0$) sells for no difference on average than similar properties in the matched control area. The other coefficients are, as discussed in Section 5.3, quite similar to our preferred specification reported in Table 5.4. Note that the coefficient before $Target_i \times Distance_i$ now is significant at 10% level. This indicates the price difference before redevelopment between target and control area indeed increases with the distance to the nearest redeveloped shopping center in the propensity score matching setting. The external effects after redevelopment is also very close to our results in column (3) of Table 5.4. The price of a property sold just after redevelopment and just next to the shopping center increases by 1.38%, which is really close to the 1.43% in our baseline regression. Similar as Table 5.4, the external effect decreases over time and it decreases faster if the property is closer to the redeveloped shopping center.

Table 5.9: Regressions results based on propensity score matching

	(1)	(2)	(3)
Target area	0-1,000 <i>m</i>	0-1,000 <i>m</i>	0-1,000 <i>m</i>
Control area	Prop. score	Prop. score	Prop. score
Target	-0.0499 (0.102)	0.0727 (0.0686)	0.0876 (0.0695)
Target×Distance	0.000132*** (2.98e-05)	3.59e-05** (1.79e-05)	3.18e-05* (1.86e-05)
Target×Trend	-0.00355** (0.00153)	-0.00288* (0.00152)	-0.00260* (0.00135)
Target×Trend×Distance	2.96e-06 (1.80e-06)	2.54e-06 (1.77e-06)	2.32e-06 (1.64e-06)
Target×Post	0.0120* (0.00637)	0.0131** (0.00591)	0.0137** (0.00577)
Target×Post×Distance	-8.43e-06 (9.18e-06)	-1.04e-05 (8.21e-06)	-1.14e-05 (8.13e-06)
Target×Post×Trend	-0.00492*** (0.000991)	-0.00419*** (0.000913)	-0.00354*** (0.000837)
Target×Post×Trend×Distance	4.65e-06*** (1.17e-06)	3.87e-06*** (1.07e-06)	3.47e-06*** (1.05e-06)
Year fixed effects (24)	Yes	Yes	Yes
Structural characteristics (14)	No	Yes	Yes
Building periods (6)	No	Yes	Yes
Shopping center characteristics (6)	No	No	Yes
Shopping center type fixed effects (8)	No	No	Yes
Neighborhood characteristics (5)	No	No	Yes
PC6 fixed effects (110,399)	Yes	Yes	Yes
Observations	966,145	966,145	966,145
Adjusted R^2	0.874	0.939	0.939

Note: Dependent variable is the log of residential property prices. The target group refers to properties located within 1,000 *m* of a redeveloped shopping center. The control group refers now to properties located within matched neighborhoods based on propensity score matching. Compared with Table 5.4, there are more observations in the control group. Standard errors clustered at PC4 level and in parentheses. The other coefficients can be obtained from the authors.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

5.7 Conclusion

This paper investigates the external effects of inner-city shopping centers on local housing markets in the Netherlands by exploiting information on shopping center

redevelopment. Shopping centers deteriorate over time and, therefore, shopping center owners redevelop their shopping centers to maximize lifetime profits. We argue that shopping center redevelopment has external effects on surrounding neighborhoods. We expect that local neighborhoods become more attractive after the redevelopment of shopping centers. If this is the case, shopping center redevelopment can be used as a tool to combat neighborhood deprivation.

To investigate the external effects of inner-city shopping centers, we use detailed information on 273 shopping centers that have been redeveloped between 1992 and 2010 in the Netherlands. We propose a difference-in-difference hedonic price model to compare residential property prices between target and control areas before and after redevelopment. We pay special attention to the heterogeneity of shopping center redevelopment external effects across space and over time. The redevelopment of shopping centers substantially increases local residential property prices. For a property located just next to a redeveloped shopping center and sold just after the redevelopment, its price increases by about 1.43% on average. However, the positive external effects after redevelopment become smaller with increasing distance for a given moment in time (until about 1,000 *m*) and these effects decrease rapidly over time. The positive external effect of redevelopment on residential property prices goes to zero within 4 years on average. While we cannot fully address all potential concerns (e.g., endogeneity concerns of the location and timing of redevelopment), we propose several sensitivity analyses to check the robustness of our main results. The results of the sensitivity analyses are rather consistent and confirm our main results.

Although our results do not capture all external benefits and costs that shopping centers provide for the neighborhood and society as a whole, our analysis shows that redeveloping shopping centers has clear implications on local housing markets using residential property prices. It suggests that using shopping center redevelopment as a tool to combat neighborhood deprivation should be carefully considered by local policy makers because of our following findings. First, the timing of redevelopment is decided by the shopping center owner. The optimal timing of redevelopment from the perspective of shopping center owners may differ from the perspective of society as a whole. Shopping center owners have incentives to postpone redevelop-

ment. Postponing redevelopment of shopping centers may lead to urban blisters and therefore substantial welfare costs to society in terms of decreasing attractiveness of neighborhoods. This suggests that if local policy makers want to prevent urban blisters caused by shopping centers, they should come up with mechanisms to influence the timing of redevelopment. Second, shopping center redevelopment can be used as a tool to combat neighborhood deprivation as the impact of redevelopment is positively associated with residential property prices. However, these positive effects on residential property prices are rather local and they decrease quickly over time.

Despite the fact that our analysis of the dynamics of the before redevelopment effect illustrate some information about the anticipation effects, we are not making any certain conclusions about the existence of anticipation effects. These place-based investments usually need a long period of time to complete. Therefore, the redevelopment of shopping centers might have anticipation effects on nearby property prices. However, from our dataset, we only have information about when the redevelopment project is completed, without any knowledge about the announcement or starting date of the project. Therefore, we are unable to identify the anticipation effects. If there are indeed anticipation effects, this would imply that our key finding, the external price effect after redevelopment, is best interpreted as a conservative lower bound estimate. Another potential issue that might be important is that some properties are within the target area of multiple redeveloped shopping centers. There might exist some bias if a property is treated multiple times. However, we leave this issue, together with the anticipation effects, for future research.

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Appendix 5.A An example of redeveloped shopping centers

Figure 5.4: ‘Amsterdamse Poort’ shopping center

Note: This is an example of a redeveloped inner-city shopping center used in our paper. As depicted in the figure, we draw polygons for redeveloped shopping centers according to their actual shapes and sizes. This means target areas are not necessarily circular. The distance from a residential property to the nearest redeveloped shopping center is calculated as the shortest distance from that property to the polygon’s edge of corresponding shopping center.

Appendix 5.B Non-random selection of redevelopment

As depicted in Section 5.3, the nonrandom selection of redeveloped shopping centers is one of our major concerns. Those shopping centers that got redeveloped may not be chosen randomly but affected by neighborhood characteristics. We are mostly concerned that the decision to redevelop may be affected by nearby property prices. It may be that shopping center owners are more inclined to redevelop their shopping center if the surrounding neighborhood's attractiveness is increasing. We test for this type of endogeneity by investigating whether neighborhood characteristics have any effect on the probability of a shopping center being redeveloped. For this purpose, we propose a logit model.

We take advantage of all shopping centers in our dataset, including redeveloped and unredeveloped ones. We gathered neighborhood characteristics from 1995 to 2010 of all the neighborhoods in which our shopping centers are located. These neighborhood characteristics include population density, the percentage of young people (<25 years old) and elderly people (>65 years old), average income⁹⁰, average propertyhold size and the percentage of immigrants⁹¹. Table 5.10 shows the summary statistics of neighborhoods included in the logit model.

By using the NVM dataset, we calculate the 5-year moving average property price of each neighborhood in every year. For example, for a neighborhood in 2004, we take the average of its average property price from 2000 to 2004 as its 5-year moving average property price. By doing this, we can capture the trend of property price in each neighborhood. In this way, we can avoid potential bias, which may be caused by unobserved variables, in our estimation results.

A binary dependent variable—let us call it, redeveloped—is generated, which equals one if a shopping center is redeveloped in the corresponding year and zero otherwise. We include the opening year of the shopping center, year fixed effects and urbanity fixed effects as control variables. The aim of this exercise is to figure out whether the neighborhood characteristics are related to the probability of a shopping

⁹⁰Neighborhood average income is measured in Dutch guilders before 2000. We transfer them into euros.

⁹¹After 2004, in the Statistics Netherlands neighborhood dataset, the percentage of immigrants is divided into two parts-western immigrants and non-western immigrants. We add them up to make sure it consistent with earlier years.

Table 5.10: Summary statistics of neighborhoods used in logit regression

	Mean	Std. Dev.	Median	Min	Max
Population density per km^2	4,910.995	2,676.539	4,627	8	24,652
Average household size	2.393	0.551	2.4	0.65	4
Average income per resident (in 1,000 euros)	12.96	4.947	11.39	3.62	44.6
Moving-average property price (in 1,000 euros)	157.748	69.911	146.900	21.124	645.486
Young people (<25 years) (%)	27.426	6.809	28	2	56
Elderly people (>65 years) (%)	17.698	10.108	16	0.5	76
Percentage of immigrants	12.683	13.002	8	0.5	87
Opening year	1983	12.723	1982	1885	2010
Redeveloped (1=yes)	0.018				
Urbanity					
Class 1 (1=yes)	0.195				
Class 2 (1=yes)	0.341				
Class 3 (1=yes)	0.217				
Class 4 (1=yes)	0.134				
Class 5 (1=yes)	0.115				
Number of observations	9,463				

center being redeveloped. Table 5.2 shows the results of the logit models. For column (1), we drop all observations with missing values on the right-hand side. Column (2) shows the results with using interpolation to replace some missing values.⁹²

Table 5.2 indicates that most neighborhood characteristics are not related to the probability of a shopping center being redeveloped. Especially, the moving average property price has no significant influence. This soothes our concern for nonrandom selection to a large extent. Furthermore, there may still exist omitted neighborhood characteristics that have an influence on the location of redevelopment. But this seems not to be a severe problem since the robustness check in Section 5.6 shows quite consistent results with our baseline specification.

⁹²We apply interpolation to every right-hand side variable on year for missing values in these variables. We perform this calculation separately for each shopping center.

Table 5.11: Logit regression results

	(1)	(2)
	Logit	Logit
Moving-average property price (in 1,000 euros)	-1.31e-06 (2.46e-06)	-2.16e-06 (1.76e-06)
Population density per km^2	2.29e-05 (3.54e-05)	-1.85e-06 (2.94e-05)
Young people (<25 years) (%)	-0.00797 (0.0318)	-0.00231 (0.0235)
Elderly people (>65 years) (%)	0.00906 (0.0145)	0.00693 (0.0108)
Average income per resident (in 1,000 euros)	7.63e-05 (0.0717)	0.0395 (0.0467)
Average propertyhold size	0.753 (0.463)	0.430 (0.338)
Percentage of immigrants	0.00756 (0.00907)	0.00953 (0.00690)
Open year	-0.0348*** (0.00573)	-0.0340*** (0.00450)
Constant	63.20*** (11.37)	62.16*** (8.925)
Urbanity fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	9,463	13,905
Pseudo R^2	0.083	0.0672

Note: The dependent variable is redeveloped, which equals one if a shopping center is redeveloped in the corresponding year; otherwise zero. Standard errors in parentheses.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Appendix 5.C The development of residential property prices in target and control areas

Figure 5.5: The development of average property prices

Note: This figure shows the development of average residential property price (upper panel) and the development of average residential property price per m^2 (lower panel), both in target and control areas. Both average property price and average property price per m^2 are calculated using property prices in our sample. This figure shows that property prices of target and control areas basically follow the same pattern.

Appendix 5.D Change of the average external effects after redevelopment and confidence intervals

Figure 5.6: Changes of external effects after redevelopment and their confidence intervals

Note: This figure shows the change of the external effects after redevelopment and their confidence intervals. From upper left to lower right panel, it represents 1 year after redevelopment to 4 years after redevelopment separately. Ninety percent significance level is used for confidence intervals.

Chapter 6

Discussion and Conclusions

This chapter concludes this thesis. In Section 6.1, we summarize the main findings from the previous chapters. Section 6.2 discusses the implications of our findings for policy. Finally, in Section 6.3, we acknowledge the limitations of this thesis and offer suggestions for future research.

6.1 Research findings

As explained in Chapter 1, the retail sector plays an important role in society and the economy. The stable development of the retail sector has important ramifications. Today, the bricks-and-mortar retail sector is facing a lot of challenges, mainly as a consequence of the rapid development of online shopping. One can predict that the decline of the physical retail sector may have serious societal and economic consequences. To successfully cope with the changing context and associated challenges, it seems crucial to improve our understanding of the retail sector. The aim of this thesis research was to gain greater insight into the physical retail sector by answering the following main research question: what are the consequences of the changing retail landscape in urban areas? This overarching question was broken down into four sub-questions and associated research topics: the location patterns of retail properties; tenant mix within shopping districts; real estate depreciation; retail revitalization and inner-city deprivation. The findings on each topic are now presented in the following subsections.

6.1.1 Location patterns of retail properties

The objective of the research reported Chapter 2 was to explore the location patterns of retail properties. It is widely recognized that the retail sector has a tendency to cluster. Through this clustering of retail properties, both retailers and consumers can benefit from shopping externalities. It is possible that different retail segments may show variations in their clustering preferences based on the characteristics of the goods and services that they provide. The clustering preferences of each retail segment should be apparent from the location patterns of the retail properties.

To investigate the location patterns of retail properties from different retail seg-

ments, we utilized granular data of retail properties from 14 retail segments in the Netherlands and analyzed these using a distance-based methodology developed by Duranton & Overman (2005) to estimate the distribution of retail properties. The underpinning idea behind this methodology is to compare the distribution of pairwise distances between every two retail properties in a retail segment with the distribution of pairwise distances of all possible retail properties in the retail sector. Compared with other approaches for estimating geographical distributions, this methodology has two advantages. First, it is independent of any geographical scale or spatial agglomeration because it uses pairwise distances between every two retail properties thereby making geographical scales irrelevant. Second, by constructing counterfactuals of retail properties, it is possible to calculate global confidence intervals for the distance density, thereby providing an indication of the significance level of the results.

Using the granular data of retail properties in the Netherlands, we saw that retail properties in retail segments that provide specialized and heterogeneous goods and services are more concentrated in terms of location than outlets for retail segments that provide homogeneous goods and services which are more dispersed. We then compared the location patterns of newly opened retail properties with those of existing retail properties because the literature provided evidence that the location decisions of real estate properties are not persistent but rather dynamic over time (Duranton & Overman, 2008; Zhou & Clapp, 2015). We were interested to see if this held for the retail sector specifically. We concluded that for retail properties in most retail segments, newly opened retail properties are more dispersed than existing retail properties. Finally, within this subtopic, we considered the location patterns of retail properties related to those of employees in the retail sector. We compared the location patterns of male employees to those of female employees in each retail segment and found that the location patterns of male employees are more dispersed than those of female employees in most retail segments.

6.1.2 Tenant mix within shopping districts

In Chapter 3, we consider the tenant mix within shopping districts. Shopping districts are formed as a result of the clustering or concentration process of retail properties. Chapter 3 focuses on the tenant mix within shopping districts and answers the question as to how tenant mix is related to the attractiveness of a shopping district.

In order to discuss tenant mix within shopping districts, the necessary first step is to define the boundaries, shapes, and sizes of shopping districts. Here, our strategy was to take advantage of the granular data on retail properties registered at the Dutch Chambers of Commerce. We defined grids for the entire Netherlands and for each grid square we calculated the kernel density of retail properties. All grid areas with a kernel density above a certain threshold were retained and adjacent grid areas were merged to form shopping districts. Notably, we repeated this procedure using data for every year between 1996 and 2011 so that we are able to capture the dynamic development of shopping districts over time. The tenant mix of each shopping district was calculated using the reciprocal of the Herfindahl Index, which was calculated using SBI information related to the granular retail property data. The second step was to investigate the relationship between tenant mix and the attractiveness of a shopping district. For this, we utilized another dataset that included rental transaction information on retail properties in the Netherlands from 1996 to 2011. Retail rents of properties in a shopping district can be used as a proxy for the attractiveness of a shopping district on the basis that the attractiveness of a shopping district should be capitalized into, and reflected in, retail rents (Pashigian & Gould, 1998; Cho & Shilling, 2007; Arzaghi & Henderson, 2008; Ahlfeldt et al., 2015). We then applied a set of different regression models to identify the relationship between tenant mix and retail rents. First, we estimated both linear and semiparametric regressions for rental transactions within shopping districts to extract the relationship between tenant mix and retail rents. Second, we applied a difference-in-difference model to control for unobserved heterogeneity in retail rents.

This analysis identified a positive relationship between tenant mix and retail rents. Shopping districts with a broader tenant mix had higher retail rents than shopping districts with a narrower range of tenants. The results from the semiparametric

regression show that this positive relationship is not constant in terms of slopes and coefficients. The difference-in-difference model confirms previous conclusions that the heterogeneity in retail rents is largely explained by the variation in the tenant mix of shopping districts.

6.1.3 Real estate depreciation

In Chapter 4, we examine the depreciation of real estate properties. Real estate properties will gradually lose their value with aging. It is important to investigate this issue to have a better understanding of the life cycle of retail properties. Moreover, in Chapter 4 we broaden our horizon slightly by focusing not just on retail properties but on all types of commercial real estate properties since depreciation applies to all types of real estate properties and variations in depreciation rates could influence investment decisions.

To investigate this topic, we made use of a commercial property sales dataset containing more than 8,000 commercial property transactions across 16 European countries from 2003 to 2017. In this research, we focused on variations in depreciation rates across regions and market segments, and the interplay between depreciation rates and the economic conditions of regional markets. We first investigated the variation in the depreciation rates of commercial properties from different European countries. We found substantial cross-sectional variations in depreciation rates across market segments and countries. We further investigated the link between depreciation rates and regional (i.e., national) economic drivers (disposable income, real GDP, and unemployment rate). We found that office properties showed negative correlations between all three economic drivers and depreciation rates, while only two of the economic drivers (disposable income and unemployment rate) have significant negative relationships with the depreciation rates of industrial properties. However, when it came to retail properties, the analysis produced insignificant interaction terms indicating an absence of a significant relationship between depreciation rates and economic drivers.

6.1.4 Retail revitalization and inner city deprivation

In Chapter 5, the topic examined relates to retail revitalization and inner-city deprivation. One of the possible outcomes for a steadily deteriorating real estate property is that it is demolished or redeveloped. Chapter 5 studies the redevelopment of retail properties by examining almost 300 shopping centers that were redeveloped between 1992 and 2010 in the Netherlands. The focus of this research was the external effects associated with the redevelopment of these shopping centers on nearby residential property prices. We used a difference-in-difference empirical framework to compare nearby residential property prices before and after the redevelopment. We were especially interested in the dynamics of the external effects, and investigated these by incorporating spatial and temporal interaction variables into our difference-in-difference framework. This was on the assumption that residential properties located closer to a redeveloped shopping center would experience a greater influence. Further, because of the depreciating pattern in real estate values, one would expect the external effects of redevelopment to decrease over time.

Our findings indicated that, before redevelopment, residential properties located within 1,000 *m* of shopping centers sold for less than comparable properties located further away. However, after redevelopment, the price of residential properties within 1,000 *m* of shopping centers increased more than comparable properties located further away. A residential property located close to a redeveloped shopping center and sold just after the redevelopment was completed would show a price increase of about 1.43% compared to similar properties that were more than 1,000 *m* away. However, our results also showed that the external effects of redeveloped shopping centers were rather local and diminished rapidly across space and over time.

6.2 Policy implications

In this thesis, we have addressed various topics related to retail real estate. As outlined in Chapter 1, the retail sector is facing many challenges. The aim of this thesis has been to gain a greater insight into retail real estate, with a special focus on retail

real estate in urban areas where retail amenities tend to be concentrated, with an overall aim to provide knowledge that can help overcome the difficulties facing the retail sector and promote the development of retail real estate. As such, our findings are not only of interest to researchers but also to real estate investors and policy makers. In this section, we discuss the policy implications of our findings.

First, from our research into the location patterns of retail properties in Chapter 2, we show that the location patterns of retail properties in those retail segments that provide specialized and heterogeneous goods and services are more concentrated than those in retail segments that provide homogeneous goods and services which are more dispersed. This confirms the heterogeneity in location patterns of retail properties from different retail segments. The implication for investors is that, when they invest in retail properties, they should consider the location patterns of the retail segments in which they are planning to invest and the distribution of retail properties in that segment in the vicinity of planned investments. This research also found that newly opened retail properties are more dispersed than existing retail properties. This could be related to the fact that public planning guidelines in the Netherlands impose strict limitations on the allowable functions of real estate properties. As such, it can be difficult for a new retail tenant to find a retail property that is close to existing retail properties. This constraint should be borne in mind, at least in the Netherlands, when considering potential investments.

Second, from our analysis in Chapter 3, we found that having a good tenant mix in a shopping district has a positive relationship with retail rents. This suggests that it may be important to maintain the diversity of retailers within a shopping district to keep it attractive. However, the ownership of retail properties in shopping districts tends to be very fragmented, which means that the tenant mix of a shopping district is usually determined exogenously and beyond the control of individual investors. This suggests that policymakers could have an important role in creating an attractive shopping district. To create a diverse and attractive shopping district, policymakers should encourage different types of retailers that provide various goods and services to have a presence.

Third, from our research on depreciation rates for commercial real estate properties in Chapter 4, we show that the depreciation rates of commercial real estate vary

across regions. We relate the differences in depreciation rates to regional economic drivers and show that depreciation rates are negatively related to unemployment rate and disposable income. This implies that it may be important for investors to carefully consider the regions in which they want to invest. Furthermore, it suggests that it may be most attractive for investors to invest in commercial real estate properties that are in a region with a high GDP, a low unemployment rate, and a high disposable income in that their properties are then less likely to be affected by depreciation and maintain their values for longer.

Finally, our research into the redevelopment of shopping centers in Chapter 5 has two important policy implications. The first concerns the timing of redevelopment. Our findings show that, when a shopping center is aging, residential properties close to the shopping center attract lower prices than similar properties that are further away and that this price differential increases over time. This suggests that shopping centers may have already become a blight on the neighborhood before the shopping center owners make the decision to redevelop the shopping center. Given the costs involved in redevelopment, shopping center owners have an incentive to postpone redevelopment. However, postponing redevelopment has social welfare costs to the neighborhood and reduces its attractiveness. This suggests that if policymakers want to reduce the harm that an aging shopping center causes in a neighborhood that they need to find a mechanism to stimulate shopping center owners to redevelop their shopping centers more regularly. Second, our findings show that, after redevelopment, the prices of residential properties located within 1,000 *m* of a redeveloped shopping center increase relative to similar properties further away. This suggests that shopping center redevelopment could be used as a tool to combat neighborhood deprivation. However, on a note of caution, this positive effect is rather local and diminishes fairly quickly over time.

As discussed in Chapter 1, the outbreak of COVID-19 may well have worsened the situation of the offline retail sector. First, the pandemic is interrupting the daily operations of the retail sector; and, second, the pandemic is also accelerating the change in consumer behavior towards online shopping. As such, the influence of COVID-19 on the retail sector may be more than a short-term disruption but herald a long-term and permanent change. It is therefore important to consider what the

retail sector could do in the face of these challenges in the post-pandemic era, and what our research suggests could be viable avenues. First, one of the advantages of the retail sector over online shopping is that the physical retail sector can provide consumers with a better shopping experience. When consumers visit bricks-and-mortar stores, they can not only buy the goods that they need but also enjoy all kinds of services to satisfy their social and entertainment needs. Therefore, the retail sector should try to both improve consumers' in-store shopping experience and also their ability to offer diverse services that fulfill consumers' social and entertainment needs. Second, investors and policymakers should promote the development of shopping centers and shopping districts that provide a broad range of goods and services. Then, by visiting shopping centers and shopping districts, consumers can be offered a wide selection of choices, and also save transportation costs and time.

6.3 Limitations and suggestions for future research

In this section, we consider some of the limitations about our research and offer suggestions for future research.

First, in our research on the location patterns of retail properties, the focus was on the clustering of retail properties in the same retail sector and the clustering of retail properties from different retail segments was not considered. However, as suggested by our later research on tenant mix, the clustering of retail properties from different retail sectors plays a very important role in determining the attractiveness of a shopping district. It is thus important to understand the tendency to cluster, or the co-location patterns, of retail properties from different retail sectors. The products of some retail sectors may be complementary to each other and, in this case, we might expect retail properties from these sectors to be inclined to cluster together. On the other hand, if the products from certain retail sectors are substitutes for each other, retail outlets from these sectors might be dispersed to avoid direct competition. Although researching co-location patterns of retail properties from different sectors will be more challenging than our within-sector study, it could provide greater insight into how retail properties are clustered.

Second, we used the reciprocal of the Herfindahl Index to measure tenant mix.

Although we demonstrated the robustness of our results in Chapter 3 by comparing this index with some other indices to measure tenant mix, it could be argued that none of these indices are perfect and, even, that the positive relationship we found between tenant mix and retail rents may be a consequence of the way we calculated these indices. There continue to be new methodologies advanced for measuring diversity and tenant mix and one of the most astonishing involves machine learning. It would be very interesting and possibly revelatory to revisit the topic of tenant mix in shopping districts using a machine-learning method to measure tenant mix.

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Finally, in our analysis of the effects of redeveloping shopping centers, we assumed that all redevelopment projects are completed within a calendar year. However, in reality, from the announcement of a redevelopment project to the completion of the redevelopment is usually a much longer period. It is reasonable to suspect that there may be anticipation effects on local housing markets following the announcement of shopping center redevelopments. However, we were unable to identify anticipation effects because we were unable to obtain information on when redevelopments were announced or started. If such data could be gathered, it would be possible and relevant to assess any anticipation effects linked to the redevelopment of shopping centers.

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Samenvatting

De detailhandel, die alle economische activiteiten betreffende de levering van goederen en diensten aan consumenten en huishoudens omvat, is wereldwijd van groot belang. De sector speelt een cruciale rol in waardeketens en biedt veel werkgelegenheid. De ontwikkeling van de detailhandel is bepalend voor moderne stedelijke gebieden en biedt legio investeringsdoelen voor investeerders. Ondanks zijn historische belang heeft de detailhandel op dit moment te maken met een groot aantal bedreigingen, met name door de snelle ontwikkeling van het online winkelen en de daarbij behorende veranderingen in consumentengedrag. Om de huidige problemen het hoofd te bieden en voorbereid te zijn op de toekomst, is een diepgaande en grondige kennis van de detailhandel nodig. Het doel van dit proefschrift is dan ook om meer inzicht te krijgen in de detailhandel en antwoord te geven op de belangrijkste onderzoeksvraag:

“Wat zijn de gevolgen van het veranderende winkellandschap in stedelijke gebieden?”

In dit proefschrift beantwoorden we deze onderzoeksvraag aan de hand van vier studies die betrekking hebben op vier aspecten: (a) locatiepatronen van winkelvastgoed; (b) huurdersmix in winkelgebieden; (c) waardedaling van onroerend goed; (d) revitalisering van de detailhandel en verschraling van binnensteden.

De eerste studie in dit proefschrift is gericht op locatiepatronen van winkelvastgoed in Nederland. Winkels hebben de neiging tot clusteren. De voorkeuren van winkels wat betreft die clustervorming kunnen echter per winkelsegment verschillen. In deze studie onderzoek ik de locatiepatronen van verschillende soorten winkels

aan de hand van granulaire gegevens over winkelvastgoed in veertien winkelsegmenten in Nederland en aan de hand van een afstandafhankelijke 'kernel-density'-methodologie. Ik stel vast dat winkelsegmenten die gespecialiseerde en heterogene producten en diensten leveren, de neiging hebben om meer te clusteren. Ook zijn pas geopende winkelobjecten in de meeste winkelsegmenten meer verspreid dan bestaande objecten. Mannen die werkzaam zijn in de detailhandel, ten slotte, zijn meer geneigd tot clusteren dan vrouwen.

De tweede studie is gericht op de huurdersmix in winkelgebieden. Stedelijke gebieden hebben al sinds lang winkelgebieden waarin winkels geconcentreerd zijn. Gesteld wordt dat de diversiteit van huurders van winkels, vaak de 'huurdersmix' genoemd, zou bijdragen aan het imago en de aantrekkelijkheid van de binnenstad. Deze winkelcentra worden gekenmerkt door versnipperd eigendom, waardoor de huurdersmix buiten de invloedssfeer van particuliere vastgoedbeleggers valt. Ik wil de relatie onderzoeken tussen de huurdersmix en huurprijzen van winkels door winkelstraten in Nederlandse stadcentra te bestuderen. Ik begin met het afbakenen van hoofdwinkelstraten aan de hand van granulaire gegevens over de ruimtelijke verdeling van werkgelegenheid in de detailhandel. In elk winkelgebied wordt de huurdersmix gemeten op basis van gedetailleerde informatie over de SBI-bedrijfsindeling en het aantal winkelobjecten. Ik stel vast dat de huurprijzen in winkelgebieden met een hogere huurdersmix hoger zijn dan in gebieden met een lagere huurdersmix.

De derde studie is gericht op waardedaling van onroerend goed. In die studie worden regionale verschillen onderzocht in afschrijvingssnelheid van commercieel winkelvastgoed in Europa. Ik bepaal de netto-afschrijvingssnelheid door verkoopprijzen voor oud en nieuw vastgoed met elkaar te vergelijken en deze in verband te brengen met de regionale economie. Ik maak gebruik van een grote steekproef van verkopen van commercieel vastgoed in Europa van 2003 tot 2017. Ik stel aanzienlijke regionale verschillen vast wat betreft de afschrijvingssnelheid, en stel ook vast dat deze per marktsegment verschillen. Ik onderzoek regionale verschillen in afschrijvingssnelheid door dieper in te zoomen op regionale economische factoren, zoals besteedbaar inkomen, het reële bbp en het werkloosheidscijfer. Ik stel vast dat vastgoedmarkten met een lagere afschrijvingssnelheid ook de markten zijn waar de

waarde van economische factoren hoger ligt of sneller stijgt.

De vierde studie is gericht op de revitalisering van de detailhandel en de vershraling van binnensteden. Winkelcentra móeten heringericht worden om aantrekkelijk te blijven voor consumenten. In deze studie doe ik onderzoek naar de externe effecten van de herinrichting van winkelcentra op de prijzen van nabijgelegen residentieel onroerend goed. Aan de hand van een empirisch 'difference-in-difference'-kader stel ik vast dat herinrichting positieve externe effecten heeft op de prijzen van nabijgelegen residentieel onroerend goed. Ik stel vast dat de prijs van een vastgoedobject naast een heringericht winkelcentrum direct na de herinrichting gemiddeld met 1,43% stijgt. De resultaten tonen aan dat deze positieve externe effecten vrij snel tenietgedaan worden naargelang de afstand groter wordt en de tijd verstrijkt. Dit wijst erop dat de herinrichting van winkelcentra een aanzienlijke, maar niet allesbepalende, rol speelt bij het tegengaan van vershraling van de wijk.

Dankzij deze studies in dit proefschrift krijgen we een beter inzicht in verschillende onderwerpen betreffende de detailhandel.