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Public Goods and Business Improvement Districts

The Economic Impacts of Business Improvement Districts in the Netherlands

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Abstract

This thesis examines the economic effects of Business Improvement Districts (BIDs) on commercial property rents and vacancy rates in the Netherlands. BIDs levy an obligatory tax on businesses, directing the proceeds toward local public goods within the district. Employing a difference-in-differences approach and hedonic price analysis, the baseline model compares rent and vacancy fluctuations between BID districts and those without BIDs. To address potential non-random selection, four alternative comparison area models are employed comprising districts that voted but did not achieve the required two-thirds majority for BID implementation, districts that used to be BIDs but that subsequently lost BID status, districts between 500m and 2000m from BIDs, and a combination of these three. Analyses are conducted for 79 industrial and 199 shopping BIDs, revealing industrial BIDs correlate with rent increases of 19% to 34%, while shopping BIDs are linked to rent increases of 2% to 15%. Shopping BIDs correlate with vacancy rate increases of 0.0005 to 0.011 percentage points, a positive impact of 0.0079 percentage points on frictional vacancy rates, and no meaningful impact on structural vacancy rates.

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1 Introduction

Rents and vacancy rates influence the retail and industrial real estate sectors considerably. Higher rents can be an advantage for property owners and investors, but may burden tenants, particularly small businesses. However, lower rents also have the potential to improve market stability by attracting a diverse range of tenants (Sivitanides, 1997). Vacancy rates indicate the equilibrium between property supply and demand, impacting property values and serve as economic indicators. Low vacancy rates instill investor confidence and support local businesses, while high vacancy rates pose challenges for existing establishments (Sivitanides, 1997). Both rents and vacancy rates play essential roles in the dynamics of real estate markets.

This thesis examines the impacts of Business Improvement Districts (BIDs) on rents and vacancy rates of retail and industrial real estate in the Netherlands. BIDs represent a policy approach that aims to optimize the provision of public goods within a municipality. A BID is referred to in Dutch as a 'bedrijven investeringzone'. In a BID, firms contribute an additional mandatory tax, which is then invested in local public goods specific to the district. The primary objective of BIDs is to facilitate the provision of local public goods by overcoming free-rider behavior through mandatory contributions from all participating firms (Briffault, 1999). Examples of local public goods that can be financed through the BID tax include security facilities, well-maintained public spaces, road signage, parking facilities, public events, and district branding.

The empirical portion of this thesis employs a difference-in-difference method to measure the economic impacts of BIDs. Specifically, it compares commercial property rents in districts that have implemented a BID with those in districts that have not, using hedonic price analyses. The thesis also compares vacancy rates, in the same way, using linear probability panel data models with fixed effects. Commercial property rents are chosen as the primary measure since they are expected to capture most of the impacts of BIDs. As BID investments are funded by companies within the district, their focus on maximizing impacts within the district is likely to be reflected in higher attractiveness and absorbed into rents. Vacancy rates are also chosen as they may capture subtleties that are potentially missed when analyzing only rents. While rents indicate the price level of occupied properties, vacancy rates provide crucial information about the overall health and demand-supply dynamics of the real estate market. They offer insights into the level of market absorption, liquidity, and property turnover, and they serve as valuable economic indicators for both investors and policymakers (Sivitanides, 1997). I use data from districts that voted to establish a BID but did not reach the required majority to allow for additional controls to account for the non-random selection of BIDs. I also use data from other comparative districts to bolster and confirm insights.

The baseline models utilize all commercial property transactions and vacancies outside of BIDs as a control group. In the second models, comparisons are made using commercial property transactions and vacancy rates in districts that voted to become BIDs but failed to reach the required two-thirds majority. Next, in the third models, comparisons are made between commercial property transactions and vacancy rates within BIDs and in areas that used to be

BIDs but that are not anymore. Then, in the fourth models, comparisons are made between BIDs and areas between 500 and 2000 meters from BIDs. Lastly, in the fifth models, all the observations in the alternative comparison areas are combined. I also explore the impacts of BIDs on structural and frictional vacancy rates, and I explore heterogeneity on vacancies in cities in the Netherlands.

The contribution of this thesis to the literature is that of an up-to-date quantitative analysis of the impacts of BIDs in the Netherlands on both rents and vacancy rates.

The structure of this thesis is as follows: first a literature review is conducted, then the research hypothesis is developed, this is followed by a discussion of BIDs and the commercial property market in the Netherlands, a discussion on the data used, a discussion of the methodology used, a review of the results, and finally, the conclusion.

2 The impacts of BIDs: a literature review

2.1 Economic theory

<u>Benefits of BIDs</u>

The primary objective of BIDs is to facilitate the provision of local public goods by overcoming free-rider behavior through mandatory contributions from all participating firms.

Local public goods are goods or services that are non-excludable and non-rivalrous, meaning they are available to all members of the community and one person's consumption of the good does not diminish its availability to others (Stiglitz, 1977). As a result of this, it is challenging to prevent people from benefiting from them and their consumption not affecting others' access. This characteristic often leads to free-rider behavior, where individuals or firms benefit from the public good without contributing to its provision. Due to this, public goods are typically provided by the government, which adjusts the level of provision and corresponding tax based on taxpayers' demand.

The challenge arises from differing demand for public goods among taxpayers and firms. It is not always clear whether the government should customize the provision to those with the lowest, median, or average demand (Samuelson, 1954). Choosing one level may not be optimal for all, resulting in suboptimal outcomes for those with higher or lower demand.

The minimization of welfare loss caused by public goods has been a subject of policy discussions. Tiebout (1956) proposed differentiating tax levels among municipalities, allowing people to sort into areas providing their preferred level of public goods. A similar sorting mechanism could also occur at the firm level. However, critics argue that this tax differentiation might lead to the segregation of rich and poor households and firms among municipalities, potentially leading to inadequate public goods provision in economically disadvantaged areas. This highlights the complexity of addressing welfare loss in public goods provision.

Drawing on insights from Kudla (2022), BIDs can therein be seen as a policy response to enable sorting at the firm level and to minimize welfare loss. BIDs and local public goods are related in various ways. BIDs are primarily a mechanism for funding and delivering local public goods. The additional taxes or assessments collected from property owners within the BID are used to finance various improvements and services that benefit the community as a whole. BIDs focus on enhancing the overall business environment and quality of life within a specific area. These improvements are available to all individuals and businesses within the BID boundaries, in alignment with the definition of public goods. By pooling resources through the BID, property owners can collectively invest in projects that may not have been feasible for individual businesses or the local government to undertake alone. By financing local public goods through the BID, stakeholders can work collaboratively to create a more attractive, vibrant, and economically viable neighborhood, thereby exemplifying collective action. While local governments are responsible for providing essential public services, BIDs can focus on specific enhancements tailored to the unique needs of the district, fostering a more tailored and responsive approach to community development.

Some examples of local public goods that can be financed through a BID tax are discussed by Park (2021). BIDs often allocate funds to improve the physical appearance and functionality of streets and public spaces within the district. This may include street furniture installations (e.g., benches and bins), pavement repairs, street lighting upgrades, landscaping, and beautification efforts. BIDs can finance initiatives aimed at enhancing safety and security within the district. This could involve hiring security guards, installing surveillance cameras, implementing crime prevention programs, or collaborating with local police. BIDs frequently allocate funds to promote the district and attract visitors and customers. Marketing efforts may include advertising campaigns, events organization, website development, and social media promotion to raise the district's profile. Also, BIDs can finance initiatives that stimulate economic growth and development within the district. This can include business attraction and retention programs, providing grants or loans to support local businesses, and offering technical assistance and training to entrepreneurs. BIDs can allocate funds for maintenance and cleaning efforts in the area. This can involve the general upkeep of public spaces. street cleaning, graffiti removal, and rubbish collection. BIDs can invest in transportation-related projects to improve access and mobility within the district. This could include parking management programs, bicycle lanes, pedestrian improvements or shuttle services. BIDs can also support public art installations and cultural events to enrich the district's cultural environment and attract visitors. Some BIDs allocate funds to support environmentally sustainable initiatives, such as energy-efficient lighting installations, waste reduction programs, and green infrastructure projects. There is a myriad of other examples of what BIDs can help bring to fruition.

In addition to providing local public goods, BIDs can also stimulate the exploitation of agglomeration economies in a district. Agglomeration economies refer to the productivity gains that arise from firms locating near one another, and they play a significant role in explaining why firms cluster spatially (Rosenthal and Strange, 2004).

Duranton and Puga (2004) propose three mechanisms for agglomeration economies: sharing, matching, and learning. The first mechanism, sharing, involves the sharing of indivisible goods or facilities, sharing the gains from variety and individual specialization, and sharing customers. Indivisible goods and facilities, such as public spaces and security facilities, can be shared among nearby firms, leading to increasing returns to scale. Sharing the benefits of variety and individual specialization relates to input-output relationships, where firms can use each other's outputs as inputs, reducing transport costs and potentially resulting in economies of scale. Customer sharing is particularly relevant for shopping districts, as customers benefit from having a variety of shops located close together, enjoying advantages of scale and scope (Claycombe, 1991).

The second mechanism of matching pertains to the labor market, where a concentration of firms and people increase the likelihood of finding suitable matches between employers and employees. The impact of BIDs on the labor market can vary depending on the specific characteristics of the district, the strategies implemented, and the broader economic and social context. Additionally, the extent of BID influence on the labor market may be influenced by the size of the BID, local government support, and the level of community engagement in the BID's activities (Elmedni et al., 2018). However, BIDs are not government entities and, therefore, lack the authority and resources to engage in labor market interventions. Labor market matching and employment-related policies are typically the purview of government agencies and workforce development organizations. The interrelation of BIDs and the labor market is not the focus of this thesis although it is a potential topic for further research.

The final mechanism, learning, involves the exchange of knowledge among employees of nearby firms, leading to improved efficiency. BIDs may facilitate the learning mechanism through meetings and events where knowledge is shared. However, in the case of Dutch BIDs the impact on learning is expected to be generally small. Most firms in Dutch BIDs are not highly knowledge-intensive, as indicated by a qualitative evaluation conducted by Berndsen et al. (2012). Consequently, the learning impact of BIDs is unlikely to significantly benefit these firms. This presumption is supported by the absence of learning-related impacts mentioned in Berndsen et al.'s evaluation, which involved interviews with BID firms.

The relevance of agglomeration economies for rents and vacancies (the focal points of this thesis) lies in the economic dynamics created by clustering businesses and amenities within the BID area. As businesses and individuals are attracted to the agglomeration benefits provided by BIDs, demand for commercial space within the district increases. This increased demand can drive up rents as property owners seek to capitalize on the appeal of the area. Higher rents are reflective of the desirability of the location and the potential for businesses to benefit from agglomeration economies (Duranton and Puga, 2004). Agglomeration economies can also contribute to lower vacancy rates in BID areas. The concentration of businesses and amenities within the district makes it an attractive location for businesses and customers, reducing the likelihood of vacant commercial spaces. The appeal of the BID area can lead to a competitive market for rental spaces, reducing the time properties remain vacant.

Agglomeration benefits within a business district are often not fully exploited due to a lack of information exchange and coordination among firms. Firms may be unaware of their shared demand for goods and facilities or lack knowledge about each other's products and services (Duranton and Puga, 2004). Moreover, even if firms possess information about potential agglomeration economies, the necessary coordination may be lacking. Coordination is required for tasks such as providing indivisible goods and facilities, optimizing customer sharing, and organizing business meetings.

A BID can enhance the exploitation of agglomeration benefits by stimulating information exchange and providing coordination. Information exchange among firms is facilitated by the requirement for firms to vote on the establishment of a BID. Initiators of the BID must persuade other firms to support it, fostering contact and information sharing. The BID association serves as a platform for further information exchange, enabling firm owners to share information and facilitating communication between firms and the municipality (Berndsen et al., 2012). Additionally, the obligatory BID tax may incentivize previously uninvolved firm owners to become engaged in the business district. Coordination is primarily managed by the BID association, which considers the interests of all firms in the district and allocates a budget for coordination costs. These costs may include expenses related to meetings, consultancy, and legal matters.

While the mandatory contributions may provide the necessary funding for public goods, they also impose financial obligations on participating firms. Therefore, the net welfare effects of BIDs should be evaluated by considering the balance between the benefits derived from improved public good provision and the costs borne by businesses.

Costs of BIDs

The long-term viability of a BID (i.e., the benefits of the BID outweighing the costs in the long term) suggests that the benefits of the BID generally outweigh its costs. If a BID becomes unprofitable, firms can vote for its discontinuation (Berndsen et al., 2012). However, it should be noted that not every individual firm may reap greater benefits than the BID tax they contribute. Nevertheless, most firms should experience positive impacts to justify the continuation of the BID. Consequently, one would expect BIDs to have favorable economic effects, potentially leading to increased commercial property rents and lower vacancy rates in the district.

However, this expectation may not always hold true due to the exclusion of incoming firms from the voting process. Only existing firms within the district are eligible to vote, which may deter incoming firms from locating in the district. This reduced demand for commercial property could result in lower rents or higher vacancy rates. Incoming firms may hesitate to participate in a BID due to the elimination of free rider behavior. Additionally, a relatively large portion of incoming firms may consist of chain shops, which typically have reservations regarding BIDs, as will be further discussed later in this thesis. The following section will explore previous research that has investigated the impacts of BIDs.

2.2 Past literature

The first BIDs were established in Canada and the USA during the 1970s in response to the declining provision of local public goods in inner cities caused by population decline. Remaining local firms collectively decided to revitalize their districts through the implementation of BIDs. Since then, the number of BIDs has gradually increased; by 2010, there were over a thousand estimated BIDs in the USA, and BIDs have been implemented in other countries such as Germany, the United Kingdom, Albania, South Africa, and the Netherlands.

Ellen et al. (2007) provided evidence on the impact of BIDs on commercial real estate values in New York City, taking an important first step in understanding the effects of these growing sub-city governments. Ellen et al. (2007) assessed the effects of 44 BIDs between 1976 and 2002. The study employed hedonic regression models to analyze the relationship between properties' sales prices and their structural characteristics, as well as their locations within neighborhoods. The study used a difference-in-difference approach to measure the impact of BIDs, comparing the price difference between BID and non-BID districts over time and examining whether this change was associated with the BID designation. The study also evaluated robustness by comparing the changes in property value of BIDs that were at that time recently established with those of BIDs that were to be established in the near future. The results indicated a significant positive impact of 17%, with notable variations among the different types of BIDs. Large BIDs and BIDs that were primarily composed of office space had large positive effects, while small BIDs and BIDs that included mostly shopping and industrial space had little impact.

Moving away from the US to the European case; according to Michel and Stein (2014), Business Improvement Districts (BIDs) in Germany and Europe in general tend to be smaller in scale and resources compared to those in countries such as South Africa or the United States. Michel and Stein (2014) found that BIDs in Hamburg, Germany have had a significant influence on public policy through their role as a lobbying tool for property owners and business interests. Due to their legal authorization to participate in decision-making processes, BIDs are considered important representatives of their respective locations. Interestingly, there does not appear to be any empirical research on the economic impacts of BIDs in Germany. The same goes for countries in Scandinavia, in southern Europe and Eastern Europe. Certainly, there has been limited empirical research on the effects of place-based policies on firm productivity in Europe and the world in general. This seems to be a general shortcoming in the literature.

Another general shortcoming in the literature is that most quantitative studies on BIDs have primarily focused on their impacts on crime rates rather than their economic effects. Hoyt

(2005) found that BIDs have significantly lower crime levels. However, a limitation of this research is the lack of control for potential selection biases. Business districts that opt into BIDs may differ from those that do not. Brooks (2008) successfully addressed this issue in her study on BID impacts on crime in Los Angeles. Using three estimation techniques, she observed significant crime declines of 5-9%. Brooks employed a neighborhood fixed-effects approach, propensity score matching based on pre-BID conditions, and comparisons with neighboring areas. Additionally, she examined the BID budget spent on reducing violent crime and found it to be at least 40% lower than the social cost of such crimes. Cook and MacDonald (2011) also investigated the social benefits of BID security expenditures in 30 Los Angeles BIDs. They measured crime counts and used the timing of BID adoption as an identification strategy. Although assuming random timing of BID adoption is arbitrary, Cook and MacDonald found that the social benefits of BID security expenditures were a large multiple (around 20) of private expenditures. They did not find evidence of spatial spillovers. These studies contribute valuable insights into the social benefits of BID investments in crime reduction, although further research is needed to fully understand their economic impacts.

De Vries (2016) investigated the economic impacts of retail and industrial BIDs in the Netherlands by looking at their effects on shopping and industrial rents (measures of productivity), respectively. De Vries (2016) baseline model used a difference-in-difference approach and a hedonic price analysis to compare rents in areas that had become BIDs with rents in areas outside of BIDs. De Vries' (2016) second model controlled for the possibility that BIDs are non-randomly selected by using an alternative comparison area: districts that voted to become a BID but that had not become a BID due to not achieving the required two-thirds majority of votes (from all the firms in the district). De Vries' (2016) third model employed a Regression Discontinuity Design using voting percentages. Only those districts with voting outcomes between 56.7% and 76.7% were used. The results indicated that industrial BIDs increase rents by 3% to 10% and shopping BIDs decrease BIDs by 3% to 12%. This second finding is strange as logically one would expect the opposite; shopping BIDs should increase rents due to the heightened attractiveness of the area. De Vries (2016) observed that this could have been because the rents of shops were adjusting to a new, lower equilibrium and also provides several other potential explanations, although is inconclusive about them. A potential endogeneity issue here is that the decrease in shopping rents may not have been caused by the negative impact of BIDs but by the delayed impact of the 2008 economic downturn that instigated the start of the BID program. It must be noted that this research was in lieu of a master's thesis and cannot be relied upon as one could with peer-reviewed research. Nevertheless, it seems to be the only empirical study directed at assessing the economic impacts of BIDs in the Netherlands.

In the literature on BIDs, a trend has emerged: the use of a difference-in-difference analysis approach is common. Poulhès (2015) observes that there is a common endogeneity problem when assessing "special economic zones": real estate within these zones is likely to be different from real estate in the surrounding areas. The difference-in-difference econometric method attempts to solve this endogeneity problem by comparing the dependent variable(s) (such as rents or prices) before and after the policy was implemented within the treated zones and non-treated zones.

In conclusion, the literature on the economic impacts of BIDs provides valuable insights into their effectiveness and the consequences arising from their implementation, in turn helping policymakers, urban planners, and stakeholders make informed decisions regarding their implementation and management in various settings. The methodology and findings of Ellen et al. (2007) provide the best theoretical basis for this thesis. De Vries (2016) provides the starting point for this thesis.

2.3 Hypothesis

Drawing on both theoretical and empirical literature, I anticipate that Dutch BIDs will yield positive economic outcomes. Empirical studies conducted in the USA have demonstrated that the establishment of BIDs leads to a reduction in crime rates and an increase in commercial property rents. Additionally, qualitative research conducted by Berndsen et al. (2012) indicates that most firms perceive the Dutch BID law favorably. This aligns with logical reasoning since BIDs operate on democratic principles, implying that firms would not lend their support if the costs outweighed the benefits.

I anticipate that the impact on property rents in Dutch BIDs will be smaller compared to the +17% on property values reported by Ellen et al. (2007) in their study conducted in New York City. There are two primary reasons for this expectation.

Firstly, institutional differences between the USA and the Netherlands are significant. As highlighted by Menger et al. (2005), the level of taxation and provision of local public goods is generally higher in the Netherlands compared to the USA. Consequently, the gap between the optimal and actual provision of local public goods is smaller in the Netherlands, limiting the potential for significant improvement and positive impact.

Secondly, the types of BIDs also play a role in determining their impact. Ellen et al. (2007) found that larger BIDs and those predominantly composed of office space tend to have larger positive impacts, whereas smaller BIDs consisting primarily of shopping and industrial spaces have limited impact. Given that Dutch BIDs mainly comprise shopping and industrial spaces, it is reasonable to expect their impacts to be less pronounced than the average New York BID.

Considering the institutional disparities and the composition of BIDs, it is therefore likely that the impact on property rents in Dutch BIDs will be relatively smaller compared to those observed on property values in the New York context.

Based on the findings of Ellen et al. (2007) and Berndsen et al. (2012), I have opted to conduct separate analyses for industrial BIDs and shopping BIDs. These studies highlight distinct impacts and differences in focus between the two types of BIDs.

Ellen et al. (2007) demonstrate that different BID types yield varying impacts. Additionally, Berndsen et al. (2012) observe a notable difference in priorities between industrial BIDs and shopping BIDs in the Netherlands. Industrial BIDs primarily allocate their budget towards park management, which prioritizes creating a safe and clean business environment. On the other hand, shopping BIDs concentrate on attracting more customers to the district through event investments and enhancing public spaces.

Given the anticipated heterogeneity in impacts and the differing emphases of these two BID types, I conduct separate regression analyses to measure the effects of industrial BIDs and shopping BIDs.

Taking into consideration De Vries's (2016) findings, I expect the effects of industrial BIDs on rents to be in a similar range (3 to 10%). However, I do not expect that shopping BIDS decrease rents as De Vries (2016) found. I expect that there will be positive impacts for rents and negative impacts for vacancy rates (lower vacancies).

I expect retail units within shopping BIDs to experience lower vacancy rates (both frictional and structural) than non-BID retail units. In other words, a negative impact.

Lastly, I expect there may be a negative impact in rents during and after the Covid-19 pandemic period (2020 onwards), specifically for retail units in shopping BIDs.

3 BIDs in the Netherlands

This chapter explores the BID law and the Dutch commercial property market. It discusses factors influencing regression results, data sources, and data cleaning methods. It presents transaction characteristics of BIDs (the treatment group) and two control groups. Regression analysis examines BIDs' impact on property market indicators.

3.1 The experimental BID law

The Dutch Experimental BID law, known as the 'Experimentenwet BI zones', was implemented in 2009. The government introduced this experiment in response to the need for financing the increasing number of district management initiatives and the positive reception of BIDs in other countries (Berndsen et al., 2012). To evaluate the effectiveness of the law before making it permanent, it was designed as an experimental measure. Consequently, BIDs were only allowed to commence on January 1st in the years 2010, 2011, and 2012. The law explicitly prohibited the establishment of BIDs in 2013 and 2014 to provide a dedicated evaluation period. In 2015, the law was made permanent, leading to a significant surge in the number of BIDs. For this research, data is available for BIDs initiated between 2010 and 2019, covering the period when the experimental law was in effect and the period after the law became permanent. As tracking data for BIDs established in 2020 onwards is unavailable (the owner of this data did not agree to share it), the focus of this study is limited to BIZs established up until the end of 2019 (but goes beyond 2019 to the present regarding commercial property transaction and vacancy data).

In order to maintain the private and voluntary nature of BIDs, a voting process is required prior to their implementation. In the Netherlands, BID voting is regulated by the following guidelines: Each firm within the BID district is granted one vote. The BID can proceed if three conditions are met. Firstly, more than half of the firms in the district must cast their votes. Secondly, at least two-thirds of the votes cast must be in favor of the BID. Thirdly, the total building values (WOZ-waarden) of the firms voting in favor of the BID must exceed the building values of the firms voting against it (Ministerie van Justitie, 2009).

According to the Dutch BID law, BIDs are obligated to hold a vote at least every five years to ensure accountability and incentivize the BID organization to deliver results. De Vries (2016) analyzed a limited period, and all BIDs included in the study were in their first term, and the concept of re-elections did not apply (Berndsen et al., 2012). However, now data are available up until the present moment in 2023 and many BIDs have gone through 1 or more re-elections, the latest ones being in 2022 and 2023.

The height and structure of the BID tax can vary among different BIDs. Some BIDs implement a uniform, fixed tax for all firms, while others have fixed taxes that differ based on the type of firm. Alternatively, taxes can be based on the building value (WOZ-waarde), with the percentage also adjustable per type of firm. It should be noted that the tax is always paid by the property user, except when the property is vacant, in which case the owner is responsible for payment (Ministerie van Justitie, 2009).

The collected taxes are administered by a BID association, led by firms from the district. The municipality collects the BID tax and returns it to the BID association. Although the municipality is allowed to deduct tax collection costs, it is more common in practice for the municipality to provide a small additional subsidy to the BID association. However, detailed information regarding these subsidies is lacking (Berndsen et al., 2012). While these subsidies may affect rents positively, they will be considered because of the BID and not controlled for in the analysis.

Table 1: Number of BIDS in the Netherlands

	Shopping BIDs	Industrial BIDs	Total
Started	199	79	278
Not started (a)	8	12	20
Ended (b)	8	12	20

Source: Buisman (2023)

(a) Districts that never became BIDs because they fell short of the required voting majority.

(b) Districts that were once BIDs but have since lost BID status.

During the analysis period (2010 to 2019), a total of 278 BIDs were established, consisting of 199 shopping BIDs and 79 industrial BIDs, as indicated in Table 1. Additionally, there were 20 (included in the analysis) districts that conducted a voting process but failed to secure the necessary two-thirds majority, thus not becoming BIDs. Berndsen et al. (2012) identified several common characteristics of BIDs, which will be discussed separately for industrial and shopping BIDs.

104 BIDs were started between the beginning of 2020 and the present. 278 BIDs were started in the 10 years between 2010 to 2019, which is an average of 27.8 BIDs started per year. In the 3.5 years from 2020, 104 BIDs were started which is an average of 29.7 BIDs started per year. Thus, the trend for BID establishment has remained fairly stable - i.e., it has not decreased or increased significantly since the pandemic.

In the case of industrial BIDs, a significant portion of the BID revenues is typically allocated to park management. Park management activities, such as collective security, road signage, and public space maintenance, are commonly outsourced to external firms. In newly developed industrial districts, the contributions for park management are often included in the rental contracts, eliminating the need for separate BIDs. As a result, industrial BIDs tend to be more prevalent in older and poorer districts. While specific data regarding the exact height of the BID tax are not available, it typically ranges between 300 and 1500 euros per year, often based on the property value.

Shopping BIDs allocate their BID tax revenues in diverse ways. Many shopping BIDs primarily focus on organizing events to attract customers to the district, while others prioritize upgrading and maintaining the public space. Interestingly, a significant number of shopping BIDs already had some form of firm cooperation before the BID was established. In these cases, the BID served to enforce cooperation and address issues related to free rider behavior.

An intriguing point highlighted by Berndsen et al. is that chain stores often vote against BIDs. This can be attributed partly to the fact that chains already engage in national advertising, making the shared marketing activities of a BID less valuable to them. Additionally, high-up chain management often lacks a comprehensive understanding of local BIDs, leading to a reluctance to contribute financially. In shopping districts, the BID tax is typically a fixed amount, approximately 300 euros.

3.2 The Dutch commercial property market

Commercial property rents and vacancy rates are used to evaluate the economic impact of BIDs. Rents and vacancies are important indicators of the health and attractiveness of a district and can provide insights into the effectiveness of BID initiatives.

Rents in the BID area can indicate the demand for commercial and retail spaces. If BID initiatives have been successful in improving the district's attractiveness, businesses may be willing to pay higher rents to locate there (Sivitanides, 1997). An increase in rents suggests that the BID's efforts in enhancing the business environment and amenities have positively influenced the real estate market.

Vacancy rates reflect the proportion of empty commercial or retail spaces in the BID area. Lower vacancy rates suggest a vibrant and active business environment, with a high demand for properties (Sivitanides, 1997). A decrease in vacancies may indicate that the BID's marketing, safety, and infrastructure improvements have contributed to attracting businesses and reducing the number of unoccupied properties.

A positive economic impact occurs when the value of BID services outweighs the costs of the BID tax (Ellen et al., 2007). To accurately measure the true impacts of BIDs, it is crucial that the idiosyncrasies of the Dutch commercial property market are taken into account. The following paragraphs explore the characteristics of the Dutch commercial property market and assess if they may affect the analysis. Since the industrial and retail property markets in the Netherlands differ significantly, they are discussed separately.

A study by Krabben et al. (2015) identifies four significant market failures in the Dutch industrial property market. The first issue relates to the decline of some industrial districts due to unpriced externalities, which is unlikely to impact price formation or hinder the research outcomes. The second problem is an oversupply of industrial districts resulting from inelastic price response and unpriced externalities. Unpriced externalities refer to the economic concept where certain costs or benefits associated with the production or consumption of goods and services are not reflected in their market prices, leading to market inefficiencies (Verhoef and Nijkamp, 2003). This suggests that it may take several years for the BID impact to be reflected in prices, which needs to be considered in the analysis. The third problem is a non-competitive market due to low land prices and limited suppliers. However, there is no evidence to suggest that the extent of non-competitiveness is linked to the likelihood of becoming a BID, so it is unlikely to bias the analysis. The last problem is the (near) absence of a market for high-end industrial property, as firms tend to build their own real estate. While this may reduce rental transactions of high-end industrial property, it is not expected to significantly affect the outcomes of the research.

The Dutch retail property market, in contrast, is relatively protected compared to the industrial property market. The location of a shop is crucial for its business, and shop owners enjoy protection in the rental market. Ending a rental contract requires a judicial procedure, and in case of a shop transfer to a new owner, the rental contract can be transferred as well. Additionally, landlords are only permitted to periodically adjust rents using a legal system that compares them to rents of similar nearby properties (Raatgever et al., 2014). Ossokina et al. (2016) mention that these laws result in rent stickiness, resulting in a time gap between an economic impact and its absorption in prices. This may introduce potential bias in the analysis, as BIDs could be initiated in districts experiencing a downturn. A measured decrease in rents or increase in vacancy rates may not necessarily be attributed to the negative impact of BIDs but could reflect a delayed impact of the downturn that prompted the BID's establishment in the first place. Consequently, controlling for potential endogeneity is crucial.

The COVID-19 pandemic accelerated e-commerce and digitalization, impacting retail real estate and the high street. Lockdowns devastated traditional retail properties but prompted the evolution of multi-channel retail, integrating physical stores with online platforms (Nanda et. al., 2021). The pandemic has also reshaped the industrial real estate sector, driven by the growth of e-commerce, supply chain adaptations, last-mile logistics, health and safety considerations, and repurposing of space (Allan et. al., 2021). Changes in consumer behavior and the urban-retail and industrial real estate landscape are expected to persist. I could have gone into a deep analysis of the impact of BIDs in the Netherlands before and after the pandemic, however, that is not the goal of this thesis. Rents and vacancies within BIDs are simply compared alongside those that are not in BIDs, before, during, and after the pandemic period in one go (more details in the methodology section).

Furthermore, Buisman (2023), who provided the BID data for this thesis, did not include BIDs that were established after 2019. So, any effects that the pandemic had on BIDs that were started after 2019 (perhaps in many cases as a response to the crisis) are not considered.

Based on the information provided, it seems that there are no significant distortions in the Dutch commercial property market that cannot be adequately controlled for in the analysis. Therefore, it is reasonable to assume that the rents reflect and absorb most of the impacts resulting from BIDs and vacancy rates may reflect other dynamics at play that give additional insights.

Ultimately, the difference in vacancy rates between BIDs and non-BID areas indicates the degree of imbalance between property supply and demand. A higher vacancy rate could mean that there are weaker market conditions and a surplus of available properties, while a lower vacancy rate could hint at stronger demand and a more competitive market (Rabianski, 2002). Differences in vacancy rates reflect local economic conditions and can influence investor sentiment. Areas with consistently low vacancy rates may be perceived as more stable and attractive for investment, while areas with higher vacancy rates may be seen as riskier prospects. However, there may be other idiosyncratic factors at work within BIDs that make these market phenomena less applicable in understanding the effects of BIDs. Nevertheless, these insights from vacancy rates (and not rents alone) will prove useful in understanding the market dynamics of real estate in BIDs.

Taking a deeper look at vacancy rates; *structural vacancies* arise from long-term imbalances between property demand and supply, while *frictional vacancies* are temporary and occur due to normal market dynamics, such as property turnover and transitional periods. (Rabianski, 2002). Structural vacancies expose fundamental imbalances in the real estate market, whereas frictional vacancies expose the time properties remain unoccupied during transitional phases. Both structural and frictional vacancies can influence property prices, rental rates, and overall market performance, making them important considerations for real estate investors, developers, and policymakers and useful points of analysis in this research.

3.3 Data

The BID data used for this thesis was collected by Buisman (2023). The dataset comprises information on all business districts that initiated the BID process between 2010 and 2019. This research focuses on the BIDs that were eventually established as well as those that failed to gain two-thirds majority support during the voting phase. It also focuses on areas that used to be BIDs and that are not anymore. To link the BID data with rental transactions and vacancies, I carefully delineated the boundaries of the BIDs in QGIS and joined the rental and vacancy point data to the BIDs using nearest neighbor analysis. Buisman's (2023) dataset did provide precise location information (as opposed to in De Vries (2016) when precise location information was not provided in the data used). De Vries' (2016) data was provided by Menger (2014) which had voting scores on all districts (which Buisman's (2023) data did not). Almost all of the BIDs in Buisman (2023) had a link to a webpage or document with an image of the map of the BID (which streets and buildings it encompasses) and these could then be mapped in QGIS. Menger (2014) did not have this. For those BIDs that this map was not available, a list of streets and/or addresses within the BID were always listed and the areas could be easily inferred from this. Therefore, the measurement error is a lot smaller than in De Vries (2016) where there was a lot more uncertainty about BID boundaries. This process revealed some minor inaccuracies in the dataset, which have been rectified. The major drawback of Buisman

(2023) is that the dataset does not provide voting percentages for the BIDs. Many of the BIDs and control areas that had voting percentages in De Vries' (2016) study have since expired, some have since become BIDs and many have changed drastically in size. For this reason, this dataset cannot be relied upon to be used for specific purposes, such as regression discontinuity design (RDD) on voting percentages.

First dataset

The commercial property transaction data (rent data) used in this thesis is sourced from STRABO (2023). Their VTIS dataset includes a significant portion of Dutch commercial property transactions. Each transaction is supplemented with building characteristics obtained from the BAG dataset, and locational characteristics derived from datasets containing information on city centers of Dutch cities with a population of over 50,000 in 2010. By combining these datasets, a comprehensive set of building and locational attributes is available for analysis.

Second dataset

The vacancy data used in this thesis is recorded by Locatus (2021). Their dataset includes a significant portion of Dutch retail vacancy data. Locatus physically inspects retail properties across the country once a year and records whether they are vacant or not. Each vacancy observation is therefore not entirely accurate as a retail unit may experience multiple vacancies within the period of a year. In other words, the data exhibit a large measurement error. While the significantly large number of observations, in this case, may reduce random errors and enhance the accuracy of estimates, it may not eliminate systematic biases or other sources of measurement error. To address this, I have used (to the best of my knowledge) as robust a research design as possible.

Since the BID dataset covers information until 2021, the analysis includes rental transactions and vacancies from 2000 to 2021. However, not all units have data from all these years.

Prior to conducting the analysis, data cleaning was performed. Firstly, for the Strabo data, observations with zero values for rent, size, or location were excluded. Secondly, for the Locatus data, the same was performed for zero values of vacancies, size, and location. Next, transactions and vacancies located within a 50-meter radius of both shopping and industrial BIDs were removed. There are two primary reasons for this exclusion. Firstly, it helps account for potential inaccuracies in the exact boundaries of the BIDs. Secondly, it addresses the possibility of spatial spillovers. For instance, a successful shopping BID may attract customers to nearby streets outside the BID boundaries, or increased security measures in an industrial BID might lead to reduced crime in neighboring areas. Studies such as Rossi-Hansberg et al. (2010) and Koster et al. (2016A) discuss spatial externalities in more depth. It is important to note that the analysis does not extensively investigate spatial spillovers, and the 50-meter buffer is chosen arbitrarily. Additionally, transactions and vacancies within the BIDs of the type not being analyzed were also dropped.

To differentiate between the analysis of industrial and shopping BIDs, specific criteria were used to filter the data. In the analysis of industrial BIDs, all transactions involving retail buildings were excluded, while in the analysis of shopping BIDs, transactions and vacancies involving non-retail buildings were excluded. Additionally, outliers in the rent values were removed to mitigate their potential impact on the regression results. For industrial BIDs, transactions with rents below 10 euros or above 500 euros per square meter were dropped. Similarly, for shopping BIDs, transactions with rents below 50 euros or above 1000 euros per square meter were dropped. This step was taken to minimize the influence of extreme values on the analysis.

Tables 2 and 3 provide an overview of the property characteristics of transactions within BIDs, outside BIDs, outside BIDs in districts that voted, outside BIDs in areas that were previously BIDs, and outside BIDs in areas between 500 and 2000 meters of a BID. Table 4 provides an overview of property characteristics for the same areas but for vacancies.

Column (1) of Table 2 presents the characteristics of transactions within industrial BIDs. These characteristics reveal that industrial BIDs are typically situated in districts with a relatively high concentration of industrial firms, which are often located further away from the city center. Furthermore, the proportion of new buildings within industrial BIDs is higher compared to those outside BIDs (column (2)). This suggests that industrial BIDs are frequently established in newer industrial areas and/or stimulate new development. The average size of an industrial property is also larger in BIDs than outside of BIDs and their average distance to the city center is slightly higher. Again, this hints at BIDs being more commonly set up in newer industrial districts that are further away from city centers and that include larger, more modern industrial buildings. The largest building type proportion in the data is by far industrial.

Table 2: Transactions characteristics: Analysis Industrial BIDs

	(1) Transactions in BIDs	(2) Transactions outside BIDs (a)(b)	(3) Transactions outside BIDs in districts that voted (a)	(4) Transactions outside BIDs in areas that were previously BIDs	(5) Transactions between 500 and 2000 meters of a BID
Built before 1900 (%)	0.28	13.93	0.00	2.43	0.28
Built between 1900 and 1945 (%)	30.48	20.07	33.73	25.4	37.05
Built after 1945 (%)	69.2	65.99	66.27	72.17	62.67
New (%)	11.97	8.87	4.31	5.87	9.19
Renovated (%)	0.85	1.44	0.39	1.83	1.95
Average size (m²)	1247.49	1020.00	361.98	815.17	463.42
Industrial building (%)	82.91	83.76	87.45	87.72	87.19
Mixed building (%)	16.52	15.89	12.55	11.47	12.53
Office building (%)	0.28	0.18	0.00	0.81	0.28
No category building (%)	0.28	0.17	0.00	0.00	0.00
Average distance to city center (km)	1.87	1.74	0.80	1.34	1.51
Transactions in the years 2010 to 2023	135	10565	123	145	124
Number of transactions in total set	351	27162	255	298	359

Source: Author's calculations based on the data used for this paper
(a) Note that this includes the transaction in BID districts before the BID was started
(b) Transactions within 50 meters of an industrial BID or transactions within and in shopping BIDs are deleted

Table 3, column (1), presents the characteristics of transactions within shopping BIDs. The analysis reveals that shopping BIDs tend to split fairly evenly between districts with older and newer buildings, as indicated by the almost equal proportion of buildings constructed before and after 1945. This suggests that about half of shopping BIDs are located within city centers and half are not. BIDs have had a lot more time to develop since they were last analyzed by De Vries (2016) and certainly most newer BIDs would logically be established in outlying areas as city centers may tend to already have BIDs. The average building size within shopping BIDs is relatively small. There could be two possible explanations for this observation. Firstly, the concentration of smaller buildings in BIDs may be a result of their central location within cities or within clustered outline retail locations. Secondly, it is plausible that BIDs are often established in districts with a limited presence of chain shops. Chain stores typically prefer larger buildings compared to local shops, which could contribute to the relatively smaller average building size within shopping BIDs.

Table **3: Transactions characteristics: Analysis Shopping BIDs**

	(1) Transactions in BIDs	**(2) Transactions outside BIDs (a)(b)**	**(3) Transactions outside BIDs in districts that voted (a)**	**(4) Transactions outside BIDs in areas that were previously BIDs**	**(5) Transactions between 500 and 2000 meters of a BID**
Built before 1900 (%)	8.86	25.28	5.65	0.41	3.24
Built between 1900 and 1945 (%)	36.80	25.56	26.12	25.31	33.25
Built after 1945 (%)	54.34	49.17	68.23	74.29	63.51
New (%)	6.36	21.80	18.275	6.12	14.08
Renovated (%)	2.93	2.02	1.65	1.22	1.70
Average size (m^2)	773.58	823.36	1004.54	1923.00	1046.71
Average distance to city center (km)	0.48	0.55	0.86	0.27	1.25
Transactions in years 2010 to 2023	996	9416	234	75	476
Number of transactions in total set	3239	23647	643	245	1236

Source: Author's calculations based on the data used for this paper
(a) Note that this includes the transaction in BID districts before the BID was started
(b) Transactions within 50 meters of a shopping BID or transactions within and in industrial BIDs are deleted

Table 4 provides an overview of the property characteristics of vacancies within BIDs, outside BIDs, outside BIDs in districts that voted, outside BIDs in areas that were previously BIDs, and outside BIDs in areas between 500 and 2000 meters of a BID.

Table 4, column (1), presents the characteristics of vacancies within shopping BIDs. The analysis reveals that buildings within BIDs built after 1945 have more than double the number of vacancies than buildings built before 1945. This suggests that there are more BIDs outside city centers than in city centers, which could mean that BIDs are often used to stimulate activity and improve public goods in quieter, outer lying shopping districts that do not benefit from the existing, inherent strong retail demand and local public goods of city centers. Again, BIDs have had a lot more time to develop since they were last analyzed by De Vries (2016) and certainly most newer BIDs would logically be established in outlying areas. This is because inner city BIDs are more likely to have already been established and new urban development tends to happen more at the urban fringe, where BIDs can be established anew.

Interestingly, in areas that voted to become BIDs but did reach the required two-thirds majority, 74.12% of vacancies are in buildings built after 1945, which suggests that the majority of these comparative areas are outside city centers. The average size of shops within these districts is also much larger than within BIDs and within the other comparison areas, which again suggests a stronger presence of large chain stores in these districts. Again, large chain stores are not incentivized to vote to be in BIDs and thus it makes sense that these comparison districts did not reach the majority vote to become BIDs. The percentage of new shops is also much higher in these districts further confirming the above.

Table 4. Vacancy characteristics: analysis shopping BIDs

	(1) Vacancies in BIDs	**(2) Vacancies outside BIDs (a)(b)**	**(3) Vacancies outside BIDs in districts that voted (a)**	**(4) Vacancies outside BIDs in areas that were previously BIDs**	**(5) Vacancies between 500 and 2000 meters of a BID**
Built before 1900 (%)	10.66	7.70	5.43	3.36	7.71
Built between 1900 and 1945 (%)	20.83	22.43	20.45	24.0	24.61
Built after 1945 (%)	68.49	69.79	74.12	72.40	67.68
New shop (%)	5.4	5.40	13.20	3.70	5.98
Average building height (m)	10.62	9.32	10.20	9.29	11.70
Average size (m²)	176.06	205.17	312.03	195.32	179.25
Number of vacancies in 2010 to 2021	16,021	161,757	3,656	2,761	9,262
Number of vacancies in total set	22,701	228,763	5,214	3,515	14,611

Source: Author's calculations based on the data used for this paper

(a) Note that this includes the vacancies in BID districts before the BID was started

(b) Vacancies within 50 meters of a shopping BID or vacancies within and in industrial BIDs are deleted

4 Methodology

This chapter focuses on the empirical analysis conducted in this paper. The first section introduces the baseline models: the first of which utilizes a hedonic regression approach and employs a difference-in-differences method to compare rents in districts that have implemented a BID with rents in districts that have not. The second baseline model looks at retail vacancies (there is no data available for industrial vacancies) and is a linear probability model that uses two-way fixed effects. The second section outlines similar models but with an alternative comparison area. The third section outlines a model similar to the first and second sections but with another alternative comparison area and the fourth section outlines the same with yet another alternative comparison area. The fifth model combines the alternative comparison areas.

4.1 Baseline model

The first baseline model (1a) employed in this study utilizes a hedonic regression approach to analyze the rents per square meter of properties, taking into account their building and locational characteristics. The second baseline model (1b) utilizes a linear probability regression approach with two-way fixed effects to find the impacts on vacancies. To measure the impact of BIDs, a difference-in-difference method is applied. This involves comparing the rents and vacancy rates in districts that have implemented a BID with the changes in rents and vacancy rates in districts that have not.

To establish causality, it is crucial to ensure that the rents in BIDs would have followed a similar trend as the rents and vacancies in the control group. In these baseline models, the control group consists of all commercial property transactions and vacancies outside of BIDs.

The analysis begins with two simple models, which serve as the starting point for assessing the impact of BIDs on rents and vacancies.

(1a) $log(R_{it}) = \gamma_0 B_{it} + \gamma_1 \bar{B}_i + a_t + \varepsilon_i$

(1b) $V_{it} = \gamma_0 B_{it} + \gamma_1 \bar{B}_i + a_t + \varepsilon_i$

The dependent variable in model (1a) is the logarithm of rent (R) for property *i* in year *t*. Using the logarithm of rents is common in hedonic models as it reduces the extreme values and improves the linearity of the regression. The dependent variable in model (1b) is the vacancy rate for property *i* in year *t*. The BID variables (B_{it}) take a value of 1 if the transaction or vacancy occurs within a BID and 0 if it does not. The focus of this research is to assess the impact of being in a BID, which is represented by the parameter γ_0.

However, since BIDs were only established from 2010 onwards, the BID variable is correlated with time. This correlation would not be a concern if rent, the dependent variable, was also not correlated with time. However, rents are likely to be influenced by time-related factors such as inflation and economic cycles. To address this omitted variable concern, year fixed effects (a_t) are included in the model. The same goes for vacancies.

Model (1a) and (1b) also incorporate "ever-in-a-BID" variables ($\bar{B}_i$). This variable takes a value of 1 if the transaction is located in a district that is already a BID or will become one in the future. The purpose of this variable is to control for characteristics specific to BID districts that may not be directly observable but can influence rents or vacancies. For instance, prior cooperation among firms in the district, such as an existing retailers' association, could lead to higher initial rents or lower vacancies compared to districts without firm cooperation. Existing strong locational characteristics are another example. While most of this difference can be captured by the postcode 4 fixed effects, the inclusion of the "ever-in-a-BID" variable accounts for any potential differences between BID borders and postcode 4 areas.

Model (1a) and (1b) assumes that the transacted buildings within BIDs are similar to those outside of BIDs. However, this is a strong assumption since the distribution of BIDs is not random across space. Firms decide to initiate a BID on their own, and it is possible that certain types of firms, located in specific buildings and areas, are more likely to start a BID. As a result, transactions and vacancies in BID districts may differ from those in non-BID districts (as shown in Tables 2 and 3). Therefore, it is important to include controls for building and locational characteristics (X_{ilt}) in the models. These characteristics can include variables such as building age, size, and the logarithm of distance to the city center. A complete specification of all control variables can be found in the Appendix in Tables A-1, A-2, and A-3.

Incorporating the building and locational characteristics into the model results in:

(2a) $log(R_{ilt}) = \beta X_{ilt} + \gamma_0 B_{it} + \gamma_1 \bar{B}_i + a_t + \varepsilon_i$

(2b) $V_{ilt} = \beta X_{ilt} + \gamma_0 B_{it} + \gamma_1 \bar{B}_i + a_t + \varepsilon_i$

Despite the improvement of models (2a) and (2b) over models (1a) and (1b), there remains a potential bias in the analysis. It is possible that BIDs are more likely to be located in districts with either higher or lower rents or vacancies compared to non-BID districts. While the locational characteristics included in models (2a) and (2b) help control for the tendency of higher rents and lower vacancies near city centers, they may not fully account for all potential unobserved variation in location.

To address this concern, models (3a) and (3b) introduce locational fixed effects (b_l). By including these fixed effects, the model captures the unobserved locational characteristics that may systematically vary across different districts. This helps to mitigate any potential bias resulting from the non-random distribution of BIDs in relation to rent levels and vacancy rates.

(3a) $log(R_{ilt}) = \beta X_{ilt} + \gamma_0 B_{it} + \gamma_1 \bar{B}_i + a_t + b_l + \varepsilon_{il}$

(3b) $V_{ilt} = \beta X_{ilt} + \gamma_0 B_{it} + \gamma_1 \bar{B}_i + a_t + b_l + \varepsilon_{il}$

An example of an unobserved locational characteristic is the proximity to the center of Den Haag, which is known for its high rents due to its popularity. Including controls for distance to city centers would not fully account for the high rents observed in Den Haag. Therefore, the introduction of locational fixed effects in models (3a) and (3b) becomes necessary to capture these unobserved differences. In this study, the locational fixed effects were implemented using the 4066 Dutch postcode-4 areas.

To address potential spatial correlation in the rental and vacancy errors, clustered standard errors based on postcode-6 areas were implemented. This approach acknowledges that errors in rents or vacancies can be spatially correlated, indicating the presence of unobserved variables that affect rents or vacancies in neighboring transactions. The use of clustered standard errors, particularly with the variation in the number of observations per postcode-6 area, helps improve the regression analysis. The standard errors were not clustered at the postcode-4 level because BIDs tend to be smaller than these areas; postcode-6 areas tend to be of a similar size or smaller than BIDs, and so were used instead.

4.2 First alternative comparison area

To address potential biases and better control for differences between districts that become BIDs and those that do not, an alternative comparison group is used in model (5). Instead of including all transactions outside BIDs as the control group, only transactions in districts that voted to become a BID but did not reach the required majority of 66.7% are considered. It is reasonable to assume that these districts experience similar trends to the BID districts, making them an appropriate comparison group.

Using these control areas, it would have been appropriate to apply regression discontinuity design (RDD) on voting percentages in control areas that are more similar in their voting as measured by the proximity of the voting score to the threshold (66.7%). However, as mentioned in the data section above, the major drawback of Buisman's (2023) dataset is that it does not provide voting percentages for all the BIDs. Many of the BIDs and control areas that had voting percentages in De Vries' (2016) study have since expired; some have since become BIDs and many have changed drastically in size, among many other minor changes. There are also many more BIDs now than in the 2016 study that simply do not have voting percentages recorded. For these reasons, this RDD cannot be applied.

Model (5a) for rents and (5b) for vacancies use the same specifications as models (3a) and (3b), respectively. The "ever-in-a-BID" variable is dropped from the models since its influence is captured by the location fixed effects because of collinearity.

4.3 Second alternative comparison area

To address potential biases and better control for differences between districts that become BIDs and those that do not, a second alternative comparison group is used in models (5a) and (5b). Instead of including all transactions outside BIDs as the control group, only transactions and vacancies in districts that used to be BIDs but that are no longer are used. It is reasonable to assume that these districts experience similar trends as the BID districts up until the point where they ceased to be BIDs, after which their trends may diverge, making them an appropriate comparison group.

Model (6a) for rents and (6b) for vacancies use the same specifications as models (3a) and (3b), respectively. The "ever-in-a-BID" variable is dropped from the models since its influence is captured by the location fixed effects because of collinearity.

4.4 Third alternative comparison area

To address potential biases and better control for differences between districts that become BIDs and those that do not, a third alternative comparison group is used in models (6a) and (6b). Instead of including all transactions outside BIDs as the control group, only transactions and vacancies in areas between 500 and 2000 meters from BID boundaries are used. It is reasonable to assume that these districts experience similar trends to the BID districts, making them an appropriate comparison group. The use of 500 meters as the lower bound of this range is to avoid spatial spillover effects. The use of 2000 meters as the upper bound is simply that transactions and vacancies beyond that distance can be influenced by a completely different set of spatial factors. I experimented using the values 1000, 1500, 2000, 2500, and 3000 metres. I found that at 1000 meters, the number of observations was too few (as the band was too small). Only at 2000 meters, the treatment coefficient changed and gained statistical significance (at the 1% level). Above 2000 meters, this coefficient does not change but loses statistical significance. For this reason, 2000 meters is used as the upper limit of the band.

Model (7a) for rents and (7b) for vacancies use the same specifications as models (3a) and (3b), respectively. The "ever-in-a-BID" variable is dropped from the models since its influence is captured by the location fixed effects because of collinearity.

4.5 Fourth alternative comparison area

I also combine the observations from the second, third, and fourth models and run the same analysis. This is simply to utilize a larger number of observations.

Model (8a) for rents and (8b) for vacancies use the same specifications as models (3a) and (3b), respectively. The "ever-in-a-BID" variable is dropped from the models since its influence is captured by the location fixed effects because of collinearity.

4.6 Structural and frictional vacancies

Lastly, I look at the impacts of shopping BIDs using structural (more than 3 years) and frictional vacancies (less than one year) to see if BIDs impact them differently.

Model (9a) for rents and (9b) for vacancies use the same specifications as models (3a) and (3b), respectively. The “ever-in-a-BID” variable is dropped from the models since its influence is captured by the location fixed effects because of collinearity.

5 Results

This chapter presents an analysis of the impacts of industrial and shopping BIDs on rents and vacancies, starting with a discussion of the industrial BIDs and ending with an examination of the shopping BIDs. To provide a concise overview of the BID impacts, simplified regression tables are included in this chapter. However, for a comprehensive view of the results, the complete regression outcomes for both industrial and shopping BIDs can be found in the appendix, in Tables A-1, A-2, A-3, and A-4.

5.1 Impact on industrial BIDs

Rents

Table 5 presents the results of the baseline model, where column (1) represents the outcomes of the simplest model. In this model, it is assumed that BIDs are randomly assigned and encompass an average mix of buildings. The analysis reveals that being located in an industrial BID has a positive impact on commercial property rent, with a coefficient of 0.1988. This implies an increase of 19.98% in commercial property rent, confirming the initial hypothesis based on the literature review. This result is statistically significant at the 5% level. However, the R-squared value in this case is very low (3.41%).

Table 5: Base models for industrial BIDs and rents

	(1)	(2)	(3)
Model name	Base model	Base model	Base model
Control group	All observations	All observations	All observations
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)
BID variables			
Post-BID	0.1988**	0.2036**	0.2531**
	(0.0953)	(0.0920)	(0.1131)
Ever in an industrial BID	-0.0220	-0.0106	0.0477
	(0.0584)	(0.0559)	(0.0762)
Post-BID 1-5 years	-	-	-
Post-BID 6-9 years	-	-	-
Post-BID 10-13 years	-	-	-
Controls			
Property characteristics	No	Yes	Yes
Fixed effects			
Postcode 4	No	No	Yes
Transaction year	Yes	Yes	Yes
Observations	17,078	17,078	13,860
R-squared	0.0341	0.0909	0.2358

Notes: Standard errors are clustered at the postcode-6 level and in parentheses;
*** p<0.01, ** p<0.5, * p<0.1

To further investigate this finding, property characteristics are included in the regression analysis. The introduction of property characteristics alters the impact of an industrial BID, resulting in a slightly higher positive coefficient of 20.36% (column (2)), which is also statistically significant at the 5% level. This finding confirms that the selection of BIDs is not random and that other factors related to property characteristics are influencing the outcomes. The R-squared value of the regression increases only slightly from 3.5% to 9.09% when property characteristics are incorporated. This indicates that the regression model is now explaining a larger proportion of the variation in rents, but only very slightly, further supporting the importance of considering property-specific factors in understanding the effects of industrial BIDs.

The “ever-in-a-BID” variable coefficients in columns (1), (2), and (3) are all statistically insignificant and low, hinting that industrial BIDs do not have stronger locational characteristics (or other inherently stronger characteristics) than general industrial real estate in the Netherlands.

In column (3) of the regression table, the impact of initiating an industrial BID is observed to decrease to 25.31% and is statistically significant at the 5% level. This result is obtained by including postcode-4 fixed effects. The magnitude of this impact appears reasonable and aligns with expectations. Furthermore, the inclusion of these additional variables has led to an increase in the explained variation in rents, which now stands at 23.58%. This indicates that the regression model is capturing a larger portion of the rent variation by considering the effects of postcode-4 fixed effects and the “ever-in-a-BID” variable.

Overall, these findings suggest that the initiation of an industrial BID correlates with a large positive impact (17% to 26%) on commercial property rents.

Table 6 presents the results of comparing transactions within BIDs with transactions in four alternative comparison areas.

Table 6: Alternative comparison areas for industrial BIDs and rents

	(1)	(2)	(3)	(4)
Model name	1st comparison area	2nd comparison area	3rd comparison area	4th comparison area
Control group	Voting districts	Previously in BIDs	Close to BIDs (5000-2000m)	Combination of (1) to (3)
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)	Rent m² (log)
Post-BID	0.3472**	0.1896	0.2800***	0.2853***
	(0.1395)	(0.1187)	(0.1050)	(0.1051)
<u>Controls</u>				
Property characteristics	Yes	Yes	Yes	Yes
<u>Fixed effects</u>				
Postcode 4	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes
Observations	250	162	12,459	13,826
R-squared	0.5010	0.6706	0.3992	0.4021

Notes: Standard errors are clustered at the postcode-6 level and in parentheses;
*** p<0.01, ** p<0.5, * p<0.1

In column (1), the model using the first alternative comparison area (districts that voted for a BID but did not initiate one) indicates a BID impact of 34.72% and is statistically significant at the 5% level with an R-squared of 50.10%. Interestingly, this impact is larger than that observed in the base model. These findings suggest that industrial districts that decide to vote for a BID may be experiencing a negative trend compared to districts that do not vote for a BID. This corresponds to the findings of Berndsen et al. (2012), who noted that BIDs are often initiated in older industrial districts undergoing a process of decline or deprivation.

In column (2), the model using the second comparison area (districts that used to be BIDs but that are not anymore) indicates a BID impact of 18.96%, but it is statistically insignificant with an R-squared of 67.06% This is a similar impact to the base model. These findings suggest that industrial districts that used to be BIDs may be experiencing a negative trend compared to districts that remain BIDs. This could be because going through all the trouble to initiate a BID and then reneging on that later on incurs financial, legal, and social costs that hamper productivity. Every district that did this would have ended their BID status for a reason. They may have found that the BID brought no discernible benefits, and the extra tax burden was therefore too much to bear. These districts may have been struggling more than other districts that remained BIDs and this might explain their even lower performance compared to districts that remained BIDs and that were successful.

In column (3), the model using the third comparison area (districts between 500 and 2000 meters from BIDs) indicates a BID impact of 28%, and is statistically significant at the 1% level, with an R-squared of 39.92%. This is a similar result to that of the first alternative comparison area but the R-squared is lower and so it is less reliable.

In column (4), the model using the fourth comparison area (a combination of the first, second, third and fourth comparison areas) indicates a BID impact of 28.53%, and is statistically significant at the 10% level, with an R-squared of 63%. This result is essentially the same as the result from (4) and shows that (5) contributes nothing that is of meaningful value.

All of the time-split variables and the “ever-in-a-BID” variable are dropped because of collinearity, so there is nothing to be interpreted for those variables.

Based on the outcomes of all the different models, it can be concluded that initiating an industrial BID correlates with a strong increase in rents (between 17.72% and 34.72%). This positive impact aligns with the expectations derived from the literature review.

An explanation for the statistical insignificance in column (2) could relate to the utilization of BIDs as a new means of financing existing park management, as previously mentioned. Some industrial districts may have already invested in park management before implementing the BID. In such cases, the BID may primarily serve to address free rider behavior, resulting in limited changes. This specific context could also contribute to the insignificance of the results in column (2). Additionally, the statistical insignificance of the impact in column (2) may be influenced by the relatively low number of transactions within the second alternative comparison area. Despite the inclusion of a relatively high number of BIDs in the research, transaction numbers are not evenly distributed across the BIDs and are not particularly high overall. This reduced number of transactions could diminish the statistical significance of the results.

Linking back to the literature review, businesses and individuals are attracted to the agglomeration benefits provided by BIDs, and therefore demand for commercial space within the district increases. This increased demand can drive up rents as property owners seek to capitalize on the appeal of the area. Higher rents are reflective of the desirability of the location and the potential for businesses to benefit from agglomeration economies (Duranton and Puga, 2004).

I decided to explore heterogeneity according to municipality, city, and industry. Unfortunately, all of these options had an insufficient number of observations and so no conclusions could be drawn from using this methodology.

5.2 Impact on shopping BIDs

Rents

Table 7 presents the results of the analysis conducted on shopping BIDs regarding rents. The first two regressions, columns (1) and (2), demonstrate a statistically insignificant and positive effect of the BIDs, 1.69% and 0.49% respectively. However, when postcode-4 fixed effects are introduced into the model, the BID effects become slightly larger (up to 2.67 and 3.45%, respectively) but remain statistically insignificant.

Table 7: Base models for shopping BIDs and rents

	(1)	(2)	(3)
Model name	Base model	Base model	Base model
Control group	All observations	All observations	All observations
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)
BID variables			
Post-BID	0.0169	0.0049	0.0267
	(0.0422)	(0.0397)	(0.0374)
Ever in a shopping BID	0.2305***	0.1954***	0.2288***
	(0.0241)	(0.0218)	(0.0293)
Post-BID 1-5 years	-	-	-
Post-BID 6-9 years	-	-	-
Post-BID 10-13 years	-	-	-
Controls			
Property characteristics	No	Yes	Yes
Fixed effects			
Postcode 4	No	No	Yes
Transaction year	Yes	Yes	Yes
Observations	16,382	16,382	13,604
R-squared	0.0540	0.3356	0.4994

Notes: Standard errors are clustered at the postcode-6 level and in parentheses; *** p<0.01, ** p<0.5, * p<0.1

The fact that the "ever-in-a-BID" variables have strong positive coefficients (statistically significant at the 1% level) between 12.31% and 23.05% hints at the fact that shopping BIDs are in areas that tend to have inherently strong locational (and other strong characteristics such as good retailer's associations) characteristics (stronger than the general retail units of the Netherlands).

Overall, the "ever-in-a-shopping-BID" variable is significant at the 1% level, indicating that rents in BID districts are 12.31% higher than those that are not. This finding is not surprising as BIDs are commonly established in city centers or areas where shops are clustered. In such locations, rents tend to be higher due to the central location and the agglomeration benefits between shops and other businesses.

Table 8 presents the results in column (1) when the districts that voted for shopping BIDs (but that did not meet the required majority vote to become BIDs) are considered as the control group. In this scenario, the impact of shopping BIDs remains positive (at 5.45%) compared to previous models and is statistically insignificant, with an R-squared of 47.38%.

Table 8: Alternative comparison areas for shopping BIDs and rents

	(1)	(2)	(3)	(4)
Model name	1st comparison area	2nd comparison area	3rd comparison area	4th comparison area
Control group	Voting districts	Previously in BIDs	Close to BIDs (5000-2000m)	Combination of (1) to (3)
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)	Rent m² (log)
Post-BID	0.0545	0.0832*	0.1085***	0.1513***
	(0.0461)	(0.0446)	(0.0413)	(0.0386)
Controls				
Property characteristics	Yes	Yes	Yes	Yes
Fixed effects				
Postcode 4	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes
Observations	1,954	2,101	2,656	3,520
R-squared	0.4738	0.4838	0.5044	0.5304

Notes: Standard errors are clustered at the postcode-6 level and in parentheses;
*** p<0.01, ** p<0.5, * p<0.1

The results in column (2) when the districts that used to be BIDs but that are BIDs no longer are also considered as a control group. In this scenario, the impact of shopping BIDs remains positive (at 8.32%) and is statistically significant at the 10% level, with an R-squared of 48.38%.

The results in column (3) when the districts between 500 and 2000 meters of BIDs are also considered as a control group. In this scenario, the impact of shopping BIDs remains positive (at 10.85 %) and is statistically significant at the 1% level, with an R-squared of 50.44%.

Lastly, in column (4), the observations from the first, second, third and fourth alternative comparison areas were combined. A higher positive impact (15.13%) was found (statistically significant at the 1% level) with a slightly higher R-squared of 53.04%.

All of these findings highlight that the impacts of shopping BIDs show a tendency towards positive effects (ranging between 8.32 and 15.13%). This observation provides insight into the dynamics of rental rates for shops and suggests a potential adjustment process occurring within the context of shopping BIDs. There are several possible explanations for the statistical insignificance in the first comparison area, column (2), similar to those discussed in the section on industrial BIDs. These explanations include the heterogeneity among shopping BIDs, the presence of well-functioning firm associations in some shopping districts prior to the establishment of BIDs, and the relatively low number of observations available for analysis (although granted, there are far more observations in this case than in industrial BIDs). To explore this with the data I had available, I decided to explore heterogeneity according to municipality, city, and industry. Unfortunately, all these options yielded insufficient observations and so no conclusions could be drawn from this.

The measured impacts of shopping BIDs, confirming my initial hypotheses, indicate a positive influence on rents. If rents are seen as a reflection of the productivity of a location, this would imply that shopping BIDs deliver more than they cost in terms of benefits. De Vries (2016) found a statistically insignificant negative impact of shopping BIDs, so my results contradict this. My results fall in line with economic theory.

De Vries (2016) argued that a potential explanation for his findings of negative effects could be that many shopping BIDs tended to have been established in districts that were already in decline and that BIDs were established to solve this but did not succeed in the years up until 2015. In light of this, my findings may suggest that if BIDs did indeed tend to be established in declining areas, the objective of the BIDs was eventually met (up until the present), yielding positive impacts, in areas that were initially in decline.

Berndsen et al. (2012) conducted interviews with shop owners in various districts and found that the majority expressed satisfaction with the costs and benefits of the BIDs. Additionally, most of the experimental BIDs continued beyond their initial period (as reported by bedrijveninvesteringszone.nl, 2016), indicating that a two-thirds majority of firms in those districts voted to continue the BID. It is unlikely that they would make this decision if the costs outweighed the benefits. These findings suggest that rents serve as a suitable but not perfect indicator of productivity and are in line with my hypothesis.

As with industrial BIDs, these higher rents are reflective of the desirability of the location and the potential for businesses to benefit from agglomeration economies (Duranton and Puga, 2004).

The next section looks at the impact of shopping BIDs on retail vacancies. As a reminder, I did not have access to industrial vacancy data and thus industrial BIDs were not considered.

Vacancies

Table 9 presents the results of the analysis conducted on shopping BIDs with regard to vacancy rates. All three base model regressions, columns (1), (2), and (3) demonstrate very small positive effects of the BIDs, 0.0005, 0.0039, and 0.0086 percentage points[1]. The first two results are statistically insignificant. The last result statistically significant at the 1% level.

1 Percentage points are a unit of measurement used to describe the difference between two percentages (in this case, vacancy rates and percentage impact on vacancy rates). It tells us how much one percentage value has changed concerning another percentage value. For instance, if an interest rate increases from 4% to 7%, the change is 3 percentage points (7% - 4% = 2 percentage points).

These results contradict my initial hypothesis that shopping BIDs would indeed have lower vacancy rates than all areas outside shopping BIDs.

Table 9: Base models for shopping BIDs and vacancies

	(1)	(2)	(3)
Model name	Base model	Base model	Base model
Control group	All observations	All observations	All observations
Dependent variable	Vacancy rate	Vacancy rate	Vacancy rate
BID variables			
Post-BID	0.0005	0.0039	0.0086***
	(0.0023)	(0.0026)	(0.0022)
Ever in a shopping BID	0.0053***	0.0022	0.0037*
	(0.0014)	(0.0015)	(0.0020)
Post-BID 1-5 years	-	-	-
Post-BID 6-9 years	-	-	-
Post-BID 10-13 years	-	-	-
Controls			
Property characteristics	No	Yes	Yes
Fixed effects			
Postcode 4	No	No	Yes
Transaction year	Yes	Yes	Yes
Observations	4,172,944	3,440,270	3,440,259
R-squared	0.0017	0.0046	0.0223

Notes: Standard errors are clustered at the postcode-6 level and in parentheses; *** p<0.01, ** p<0.5, * p<0.1

Interestingly, the "ever-in-a-BID" variables are positive hinting that BIDs had existing characteristics before they were BIDs that led to them having slightly higher vacancy rates than other areas. The existence of effective but selective retailers' associations could be an example of this.

Given that numerous Dutch shopping BIDs would in theory aim to reduce vacancy rates in their shopping centers, it is plausible that they employ their collective market power to achieve this goal. For example, the Jan-Eef BID in Amsterdam assists in finding new tenants for vacant properties, selecting the most suitable shop types for the district (Jan Eef, 2016). For these reasons, I expected to see negative impacts, but indeed, the positive impacts truly are very small, albeit statistically significant and all have very low R-squared values (ranging between 0.17% and 2.23%) which shows that my models do not explain the variation in vacancies very well. Nevertheless, it seems the impacts of BIDs is undoubtedly positive, which means that the effects of agglomeration economies (that of theoretically lowering vacancies) are overpowered by other dynamics within the BIDs and although BID participants might collaborate to fill vacancies, this (more selective) collaboration could also be the reason vacancies are slightly higher than other areas.

Table 10 shows the results of using the same alternative comparison area rules as in the previous two analyses on rents

Table 10: Alternative comparison areas: shopping BIDs and vacancies

	(1)	(2)	(3)	(4)
Model name	1st comparison area	2nd comparison area	3rd comparison area	4th comparison area
Control group	Voting districts	Previously in BIDs	Close to BIDs (5000-2000m)	Combination of (1) to (3)
Dependent variable	Vacancy rate	Vacancy rate	Vacancy rate	Vacancy rate
Post-BID	0.0064**	-0.0069**	0.0113***	0.0080***
	(0.0025)	(0.0030)	(0.0023)	(0.0023)
<u>Controls</u>				
Property characteristics	Yes	Yes	Yes	Yes
<u>Fixed effects</u>				
Postcode 4	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes
Observations	268,330	293,481	438,716	717,354
R-squared	0.0185	0.0206	0.0204	0.0204

Notes: Standard errors are clustered at the postcode-6 level and in parentheses;
*** p<0.01, ** p<0.5, * p<0.1

Again, these results mostly mirror the findings of the base models. The first alternative comparison area (districts that voted to become BIDs but did not reach the required majority) in column (1) yields a statistically significant (at the 5% level) positive impact of 0.0064 percentage points with a very low R-squared of 1.85%. yields. The second alternative comparison area - column (2) - (areas that used to be BIDs but that are not anymore) yields a statistically significant (at the 5% level) negative impact of 0.0069 percentage points with an ever-so-slightly higher R-squared of 2.06%. This negative impact (the only one that confirmed my initial hypothesis) could be because these areas have strong locational and other characteristics and so experienced fewer vacancies than BIDs (perhaps hinting at the very reason why they themselves ceased to operate as BIDs: they simply did not need to because the costs of being a BID outweighed the benefits). The third alternative comparison area – column (3) - (districts between 500 and 2000 meters of BIDs) yields a statistically significant (at the 1% level) positive impact of 0.0113 percentage points with an R-squared of 2.04%. The fourth alternative comparison area – column (4) - (a combination of the first, second, and third alternative comparison areas) yields a similar impact of 0.008 percentage points which is statistically significant (at the 1% level) and has a low R-squared of 2.04%.

A potential explanation for the general findings of positive impacts on vacancy rates (in contrast to the expected negative effects) could be that existing firms benefit from the BID and have a strong sense of safety in collaboration and so hinder other firms from entering the district if there is no urgent need to fill the vacancy if they feel potential tenants will not bring the desired characteristics to the table. If a collection of firms has created a very particular physical environment and culture together through the enabling qualities of a BID, they may be more hesitant to let just any firm that comes along wanting to rent in the district. They may have more stringent requirements for the quality of the tenant and in so doing, the vacancy rate remains slightly higher.

Table 11 shows the results of the impacts of BIDs on structural vacancy rates (units vacant for 3 or more years) and frictional vacancy rates (units vacant for one year or less). The full regression table is found in A-4 in the appendix. In column (2) the impacts on frictional vacancy rates are similar to the previous results: a statistically significant positive (at the 1% level) impact of 0.0079 percentage points with an R-squared of 1.07%. In other words, BIDs increase short-term (frictional) vacancy rates by 0.0079 percentage points, perhaps for the reasons stated in the above paragraph or another reason discussed below. Long-term (structural) vacancy vacancies do not seem to be affected by BIDs (judging from the minuscule, statistically insignificant negative impact of 0.1% with an R-squared of 1.76%).

The results from Table 11, column (2) on frictional vacancy rate may also be related to the process of finding the right tenants: BIDs provide very specific public goods, specific to the immediate area and landlords in the BIDs need to find the right tenants that appreciate the set of public goods (tenants that do not demand the specific set of local public goods may also be driven away), which could make the process of filling vacancies take longer, and hence leading to a higher frictional vacancy rate, whilst the structural vacancy rate remains mainly unchanged.

Table 11: Structural and frictional vacancies

	(1)	(2)
Model name	Model 9a	Model 9b
Dependent variable	Structural vacancy rate	Frictional vacancy rate
Post-BID	-0.0010	0.0079***
	(0.0012)	(0.0008)
	(0.0038)	(0.0013)
Observations	3,440,259	3,440,259
R-squared	0.0176	0.0107

Notes: Standard errors are clustered at the postcode-6 level and in parentheses;
*** p<0.01, ** p<0.5, * p<0.1

Exploring heterogeneity on shopping BIDs and vacancies

Since all of the above impacts on vacancies are so small, I decided to explore heterogeneity on industries and cities in the Netherlands to see if there were perhaps larger BID impacts in specific cities. The Locatus vacancy dataset has many more observations than the Strabo commercial rents dataset used in the first analyses of this thesis and so I was able to do this. However, there were only a sufficient number of observations to yield results on the impacts of BIDs in certain cities. Many cities did not have enough observations in them for this. I also tried to explore heterogeneity on industry types, but each industry type alone had an insufficient number of observations to yield results.

All cities above 20,000 inhabitants were tested. Those with insufficient observations were excluded. The results of the base model parameters with all the controls, fixed effects, and clustering at the postcode-6 level, filtered by city are shown in Table A-4 in the Appendix.

Itt can be observed that most of the impacts of shopping BIDs on vacancy rates are negligible and statistically insignificant. Only in two cities, Breda and Amsterdam, do BIDs exhibit a positive impact (0.0092 and 0.0356 percentage points respectively), both results being statistically significant (both at the 5% level). Not shown here (but shown in the appendix), are the coefficients of all the other controls. These results are extremely heterogenous, and every city exhibits a different trend over the three time periods and for the “ever-in-a-BID” variable. Results are only statistically significant in a limited number of instances. There are no discernible patterns in vacancy rates among cities.

6 Discussion and conclusion

Since the inception of the BID concept in the 1970s, the number of BIDs in many countries has been steadily increasing. In the Netherlands, which implemented BIDs, the concept was introduced through an experimental law. This law allowed for the establishment of BIDs from 2010 to 2012 but prohibited them in 2013 and 2014. The present thesis is based on the permanent law established in 2015 and investigates the impacts of BIDs on commercial property rents and on vacancy rates. Furthermore, the thesis contributes to the limited existing empirical evidence on the effects of BIDs.

According to economic theory, BIDs are expected to have a positive impact on rents. The democratic nature of BIDs enables the provision of additional public goods in districts where there is demand for them. Additionally, BIDs facilitate the exploitation of agglomeration economies by fostering cooperation and coordination. If the costs of a BID outweigh the benefits, firms would vote against it, leading to its dissolution.

The empirical part of the thesis examines the impacts of BIDs using a difference-in-difference approach for rents and a linear probability model for vacancies. It compares the rents and vacancies of commercial properties within implemented BIDs with similar properties outside BID districts, employing a hedonic price model (for rents) and a linear probability model (for vacancies). Both sets of models effectively use the same variables and controls. The base model employs all property transactions outside BID districts as the control group. Extensions to the model use restricted control groups consisting of districts that voted to start a BID but did not attain the required two-thirds majority, districts that used to be BIDs but that are not anymore, districts within 500 to 2000 meters from BIDs, and a combination of all of these.

The regression results indicate that industrial BIDs have a positive impact on rents between 19 and 34%. This impact appears to be causal, as most of the models are highly statistically significant. To improve the analysis of industrial BID impacts, incorporating information about park management would be beneficial. Most industrial BIDs used BID revenues to fund park management. However, some districts already had park management in place and employed the BID solely to address free-rider behavior. The impact of becoming a BID in these districts is likely to be smaller than in districts without pre-existing park management. Including information on park management could shed light on this aspect.

The regression analysis indicates that shopping BIDs have a positive and causal influence on rents, with estimated impacts ranging from 2% to 15%. Multiple models demonstrate statistically significant positive effects, including impacts of 8%, 10%, and 15% at the 5%, 1%, and 1% significance levels, respectively. These significant results, observed across different control groups in standard regression models, provide robust evidence supporting the presence of a causal relationship.

The observed impacts of shopping BIDs on vacancy rates generally show slight positive effects ranging from 0.0005 to 0.0113 percentage points, and many of these effects are statistically significant. These findings contrast with the anticipated negative (lower) effects of BIDs on vacancy rates. To gain deeper insights, I conducted further analysis to examine variations across cities and industries in relation to vacancies. However, these results do not hint at different conclusions.

A possible explanation for these positive impacts is that firms operating within BID districts may actively discourage businesses that do not meet their bespoke standards. This could be due to the improvements brought about by the BIDs in the districts and the enhanced collaboration among firms. Similarly, BIDs were found to have a statistically significant positive effect of 0.0079 percentage points on frictional vacancy rates but no discernible effect on structural vacancy rates. A more plausible reason for the positive effects is that BIDs provide very specific public goods, specific to the immediate area. Landlords in the BIDs need to find the tenants that appreciate the set of public goods, which could lengthen the process of filling vacancies (similarly, some tenants might be put off by the very specific set of public goods). The positive impacts also might mean that the expected effect of agglomeration economies on vacancies (that they are lowered) are outweighed by the dynamics discussed above.

Another possible explanation for the higher rents in BIDs is that firms in BIDs pay more tax than they would have otherwise, and this gets absorbed in the rents. Landlords must make up the additional costs and so charge higher rents.

Overall, the long-term viability of a BID (i.e., the benefits of the BID outweighing the costs in the long term) suggests that the benefits of the BID generally outweigh its costs. This is generally reflected in the findings of positive impacts on rents. If a BID becomes unprofitable, firms can vote for its discontinuation. Some BIDs did vote for discontinuation and so the findings of this thesis do not confirm that BIDs are a universal solution for all districts, and in some instances, the costs of BIDs do outweigh the benefits.

A suggestion for further research is to replicate this study in a few years. This thesis included 8 more years of data than in De Vries' (2016) research, however, BID data from 2020 onwards, up until the present moment will be useful, especially in capturing the effects of Covid-19 on BIDs that were established during and after the pandemic. It would be valuable to redo this analysis in the future when additional rent transactions have occurred. Furthermore, additional BID information and a larger number of transactions could enable the measurement of the impacts of BID characteristics; such characteristics could include size (determined by the number of firms within the BID), tax rates (of which data is available to the patient web scrawler or from surveys), types of firms/industry types and regions and cities. I found that in looking at industry types and cities, there often were not enough observations available once filtering had been applied. However, in the future, when more data is available, it will be valuable to explore heterogeneity in this regard. It would also be useful to look at the effects of BIDs on property values to see whether they exhibit the same growth as shown in rents. It would be valuable to look at the effects of industrial BIDs on industrial real estate vacancy rates (of which data I did not have access to). Furthermore, it would be insightful to explore the impacts of BIDs on local employment.

The benefits of BIDs are not necessarily only economic: it would be useful to look at the effects of BIDs on social metrics such as crime rates, footfall, and consumer and business satisfaction, amongst others.

Lastly, conducting a survey on BID-participating firms would be insightful. In this survey, questions on tax levels, voting scores, what types of local public goods were financed, and other metrics could be asked to gain deeper insights into the workings and impacts of BIDs.

References

Allan, R., Liusman, E., Lu, T., and Tsang, D. (2021). The COVID-19 Pandemic and Commercial Property Rent Dynamics. Journal of Risk and Financial Management, 14(8), 360.

Bedrijveninvesteringszone.nl. (2016). BIZ-locator. Retrieved from http://bedrijveninvesteringszone.nl/onze-diensten/biz-locator/ (Accessed 27-05-2023).

Berndsen, R., Doornbos, H., Vliet, M. v., and Maas, F. (2012). Evaluatie Experimentenwet Bedrijven Investeringszones (BIZ). Utrecht.

Briffault, R. (1999). A Government for our Time? Business Improvement Districts and Urban Governance. Columbia Law Review, 365-477.

Brooks, L. (2008). Volunteering to be Taxed: Business Improvement Districts and the Extragovernmental Provision of Public Safety. Journal of Public Economics, 92(1), 388-406.

Buisman, P. (2023). Data on BIDs in the Netherlands. Retrieved from Pieter Buisman Advies management van gebiedsontwikkeling.

Claycombe, R. J. (1991). Spatial Retail Markets. International Journal of Industrial Organization, 9(2), 303-313.

Cook, P. J., and MacDonald, J. (2011). Public Safety through Private Action: an Economic Assessment of BIDS*. The Economic Journal, 121(552), 445-462.

Duranton, G., and Puga, D. (2004). Micro-foundations of Urban Agglomeration Economies. Handbook of Regional and Urban Economics, 4, 2063-2117.

Ellen, I. G., Schwartz, A. E., Voicu, I., Brooks, L., and Hoyt, L. (2007). The Impact of Business Improvement Districts on Property Values: Evidence from New York City [with Comments]. Brookings-Wharton Papers on Urban Affairs, 1-39.

Elmedni, B., Christian, N., and Stone, C. (2018). Business Improvement Districts (BIDs): An Economic Development Policy or a Tool for Gentrification? Cogent Business and Management, 5(1).

Hoyt, L. M. (2005). Do Business Improvement District Organizations Make a Difference? Crime in and Around Commercial Areas in Philadelphia. Journal of Planning Education and Research, 25(2), 185-199.

JanEef. (2016). Activiteiten Jan Eef. Retrieved from http://www.geefomdejaneef.nl/over-janeef/activiteiten/ (Accessed 05-06-2016).

Koster, H. R. A., Pasidis, I. N., and van Ommeren, J. (2016A) Shopping Externalities and Retail Concentration: Evidence from the Netherlands. Working paper.

Koster, H. R. A., and van Ommeren, J. (2016B). Place-based policies and the housing market: Prices, Time on the Market and Welfare. Working paper.

Krabben, E. v. d., Pen, C.-J., and Feijter, F. d. (2015). De Markt voor Bedrijventerreinen: Uitkomsten van Onderzoek en Beleid. Platform31.

Kudla, D. (2022). Fifty Years of Business Improvement Districts: A Reappraisal of the Dominant Perspectives and Debates, Urban Studies, 59(14), 2837-2856.

Locatus. (2021). Locatus 2003 to 2021. https://locatus.com/en/applications/locatus-online-all-about-data-driven-retail-insights/ (Accessed 17-04-2023).

Ministerie van Justitie (2009) Experimentenwet BI-zones. Retrieved from http://wetten.overheid.nl/BWBR0025644/2014-01-25 (Accessed 25-05-2023).

Menger, J. (2014). Lijst Bedrijveninvesteringszones Nederland 1-5-2014. Retrieved from: http://biz.joostmenger.nl/ (Accessed 28-05-2023).

Menger, J. P., Zweedijk, M. Q., and Olden, H. (2005). Business Improvement District: Ondernemersinitiatief Beloond. Rotterdam.

Michel, B., and Stein, C. (2014). Reclaiming the European City and Lobbying for Privilege: Business Improvement Districts in Germany. Urban Affairs Review, 51(1), 74-98.

Nanda, A., Xu, Y., and Zhang, F. (2021). How Would the COVID-19 Pandemic Reshape Retail Real Estate and High Streets Through Acceleration of E-commerce and Digitalization? Journal of Urban Management, 10(2), 110-124.

Ossokina, I., Sviták, J., Teulings, C., and Zwaneveld, P. (2016). Winkelleegstand na de Crisis.Centraal Planbureau.

Park, W. (2021). How to Use Business Improvement Districts (BID) as a Public-Private Partnership Governance for Urban Regeneration, Journal of Real Estate Analysis, 7(2), 89-116.

Raatgever, A., and et al. (2014). Winkelgebied van de Toekomst. Platform31.

Rabianski, J. S. (2002). Vacancy in Market Analysis and Valuation. The Appraisal Journal, 70(2), 191-199.

Rosenthal, S. S., and Strange, W. C. (2004). Evidence on the Nature and Sources of Agglomeration Economies. Handbook of Regional and Urban Economics, 4, 2119-2171.

Rossi-Hansberg, E., Sarte, P.-D., and Owens III, R. (2010). Housing externalities. Journal of Political Economy,118(3), 485-535

Samuelson, P. A. (1954). The Pure Theory of Public Expenditure. The Review of Economics and Statistics, 36(4), 387-389.

Sivitanides, P. (1997). The Rent Adjustment Process and the Structural Vacancy Rate in the Commercial Real Estate Market. Journal of Real Estate Research, 13(2), 195-209.

Stiglitz, J.E. (1977). The Theory of Local Public Goods. The Economics of Public Services. International Economic Association Conference Volumes. Palgrave Macmillan, London.

STRABO. (2023). Strabo VTIS Dataset. https://strabo.nl/databases (Accessed 17-04-2023).

Tiebout, C. M. (1956). A Pure Theory of Local Expenditures. The Journal of Political Economy, 64(5), 416-424.

Verhoef, E. T. and Nijkamp, P. (2003). Externalities in the Urban Economy, Tinbergen Institute Discussion Paper No. 2003-078/3.

Appendix

(A) Shopping BIDs and control areas (B) Industrial BIDs and control areas

Figure 1: Maps showing locations of BIDs and control areas in the Netherlands

Table A-1: Regression results - industrial BIDs and rents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model name	Base model	Base model	Base model	1st comparison area	2nd comparison area	3rd comparison area	4th comparison area
Control group	All observations	All observations	All observations	Voting districts	Previously in BIDs	Close to BIDs (5000-2000m)	Combination of (4) to (6)
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)	Vacancy rate	Vacancy rate	Vacancy rate	Vacancy rate
BID variables							
Post-BID	0.1988**	0.2036**	0.2531**	0.3472**	0.1896	0.2800***	0.2853***
	(0.0953)	(0.0920)	(0.1131)	(0.1395)	(0.1187)	(0.1050)	(0.1051)
Ever-in-a-BID	-0.0220	-0.0106	0.0477	-	-	-	-
	(0.0584)	(0.0559)	(0.0762)				
Property characteristics							
Footprint	-	0.0002	0.0004	0.0009	0.0015	0.0001	-0.0001
		(0.0003)	(0.0003)	(0.0021)	(0.0015)	(0.0003)	(0.0003)
Surface (log)	-	-0.0639***	-0.0650***	-0.1013**	-0.0389	-0.0553***	-0.0589***
		(0.0062)	(0.0066)	(0.0500)	(0.0483)	(0.0063)	(0.0059)
New	-	0.3238***	0.2318***	0.0897	0.0309	0.2851***	0.2765***
		(0.0252)	(0.0274)	(0.1712)	(0.2036)	(0.0274)	(0.0264)
Renovated	-	0.2477***	0.2103***	-0.2699	-0.5446***	0.2290***	0.2212***
		(0.0666)	(0.0733)	(0.1857)	(0.1639)	(0.0673)	(0.0649)
Sale-leaseback	-	0.3416***	0.3228***	0.2737	0.1024	0.2823***	0.3065***
		(0.0705)	(0.0775)	(0.3581)	(0.4597)	(0.0756)	(0.0737)
Industrial Building	-	-	-	-0.7895***	-0.7252***	-0.8692***	-0.8638***
				(0.0996)	(0.1365)	(0.1487)	(0.1478)
Mixed Building	-	-	-	-	-	-0.1598	-0.1551
						(0.1485)	(0.1477)
Office Building	-	-	-	-	-	-0.2672	-0.2117
						(0.1791)	(0.1785)
No Category Building	-	-	-	-	-	-	-
Parking	-	0.3605***	0.2945***	0.1750	-0.0348	0.1580***	0.1644***
		(0.0174)	(0.0189)	(0.1074)	(0.1341)	(0.0158)	(0.0149)
No Parking	-	-	-	-	-	-	-
Distance to city center	-	-0.0019***	-0.0023***	0.0036	0.0156	-0.0014**	-0.0015**
		(0.0006)	(0.0007)	(0.0239)	(0.0128)	(0.0007)	(0.0007)
Construction Year	-	0.0000***	0.0000**	0.0005	-0.0001	0.0000	0.0000**
		(0.0000)	(0.0000)	(0.0019)	(0.0018)	(0.0000)	(0.0000)
Size*Building Type	-	-	-	-0.0002**	-0.0001	-0.0000	-0.0000**
				(0.0001)	(0.0001)	(0.0000)	(0.0000)
Size*Transaction Year	-	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed effects							
Postcode 4	No	No	Yes	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.2542***	4.6241***	4.6429***	4.6448	5.3890	5.3331***	5.3326***
	(0.0071)	(0.0413)	(0.0442)	(3.6981)	(3.4321)	(0.1530)	(0.1516)
Observations	17,078	17,078	13,860	250	162	12,459	13,826
R-squared	0.0341	0.0909	0.2358	0.5010	0.6706	0.3992	0.4021

Table A-2: Regression results - shopping BIDs and rents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model name	Base model	Base model	Base model	1st comparison area	2nd comparison area	3rd comparison area	4th comparison area
Control group	All observations	All observations	All observations	Voting districts	Previously in BIDs	Close to BIDs (5000-2000m)	Combination of (4) to (6)
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)	Vacancy rate	Vacancy rate	Vacancy rate	Vacancy rate
BID variables							
Post-BID	0.0169	0.0049	0.0267	0.0545	0.0832*	0.1085***	0.1513***
	(0.0422)	(0.0397)	(0.0374)	(0.0461)	(0.0446)	(0.0413)	(0.0386)
Ever-in-a-BID	0.2305***	0.1954***	0.2288***	-	-	-	-
	(0.0241)	(0.0218)	(0.0293)				
Property characteristics							
Footprint	-	0.0000**	0.0000***	-0.0000*	-0.0000*	-0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Surface Log	-	-0.3914***	-0.3487***	-0.3150***	-0.3067***	-0.3167***	-0.3212***
		(0.0068)	(0.0071)	(0.0197)	(0.0190)	(0.0165)	(0.0140)
New	-	0.0667***	0.1076***	0.1712***	0.1804***	0.1309***	0.1172***
		(0.0209)	(0.0207)	(0.0592)	(0.0538)	(0.0472)	(0.0389)
Renovated	-	0.1636***	0.1009**	0.0471	0.0888	0.0952	0.1335
		(0.0413)	(0.0436)	(0.0990)	(0.1107)	(0.0849)	(0.0884)
Sale-leaseback	-	(0.1409)	(0.0924)				(0.1744)
		-0.1808***	-0.1406***	-0.3514**	-0.3470**	-0.2387*	-0.2824***
		(0.0320)	(0.0387)	(0.1539)	(0.1378)	(0.1314)	(0.1095)
No parking	-	-	-	-	-	-	-
Distance to city center	-	-0.0014	-0.0024**	-0.0130*	-0.0093	-0.0074**	-0.0070**
		(0.0010)	(0.0010)	(0.0075)	(0.0070)	(0.0033)	(0.0032)
Construction Year	-	-0.0000	0.0000***	0.0000	0.0000	0.0000	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size*Transaction Year	-	0.0000**	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fixed effects							
Postcode 4	No	No	Yes	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.1645***	7.2075***	6.9522***	7.0490***	6.9808***	6.9880***	6.9476***
	(0.0090)	(0.0391)	(0.0391)	(0.1035)	(0.0999)	(0.0870)	(0.0741)
Observations	16,382	16,382	13,604	1,954	2,101	2,656	3,520
R-squared	0.0540	0.3356	0.4994	0.4738	0.4838	0.5044	0.5304

Table A-3: Regression results - shopping BIDs and vacancies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model name	Base model	Base model	Base model	1st comparison area	2nd comparison area	3rd comparison area	4th comparison area	Model 6a	Model 6b
Control group	All observations	All observations	All observations	Voting districts	Previously in BIDs	Close to BIDs (5000-2000m)	Combination of (4) to (6)		
Dependent variable	Rent m² (log)	Rent m² (log)	Rent m² (log)	Vacancy rate	Vacancy rate	Vacancy rate	Vacancy rate	Structural vacancies	Frictional vacancies
<u>BID variables</u>									
Post-BID	0.0005	0.0039	0.0086***	0.0064**	-0.0069**	0.0113***	0.0080***	-0.0010	0.0079***
	(0.0023)	(0.0026)	(0.0022)	(0.0025)	(0.0030)	(0.0023)	(0.0023)	(0.0012)	(0.0008)
Ever-in-a-BID	0.0053***	0.0022	0.0037*	-	-	-	-	-	-
	(0.0014)	(0.0015)	(0.0020)						
<u>Property characteristics</u>									
Size	-	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Building Height	-	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Construction Year	-	0.0000***	0.0000***	0.0000**	0.0000**	0.0000**	0.0000***	0.0000***	-0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
<u>Fixed effects</u>									
Postcode 4	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.0597***	-0.0104	0.0053	0.0246**	0.0287**	0.0273***	0.0113	-0.0041	0.0112***
	(0.0004)	(0.0069)	(0.0071)	(0.0105)	(0.0111)	(0.0102)	(0.0114)	(0.0038)	(0.0013)
Observations	4,172,944	3,440,270	3,440,259	268,330	293,481	438,716	717,354	3,440,259	3,440,259
R-squared	0.0017	0.0046	0.0223	0.0185	0.0206	0.0204	0.0204	0.0176	0.0107

Table A-4: Regression results - Heterogeneity on cities - shopping BIDs and vacancies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Control group	Amsterdam	Rotterdam	Den Haag	Eindhoven	Tilburg	Breda	Haarlem	Zwolle	Amersfoort	Deventer	Heerlen	Zoetermeer	Gorinchem	Roermond	Hengelo
Post-BID	0.0092**	0.0005	0.0091	-0.0005	0.0092	0.0356**	-0.0027	0.0115	-	0.0135	-0.0149	-0.0008	-0.0051	-0.0160	-0.0357
	(0.0041)	(0.0044)	(0.0074)	(0.0082)	(0.0126)	(0.0156)	(0.0179)	(0.0112)		(0.0397)	(0.0348)	(0.0295)	(0.0168)	(0.0180)	(0.0723)
Ever-in-a-BID	0.0052	-0.0093**	-0.0091	-0.0090	-0.0282***	0.0109	0.0130	-	-0.1043	0.1405***	-0.0028	0.2295***	-	-	-
	(0.0037)	(0.0041)	(0.0082)	(0.0075)	(0.0091)	(0.0118)	(0.0193)		(0.1923)	(0.0154)	(0.0097)	(0.0105)			
Size	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000	-0.0000***	-0.0000	-0.0000	-0.0000*	-0.0001**	-0.0000*	-0.0000	-0.0000***	-0.0000**	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Building Height	0.0000***	0.0000***	0.0000***	0.0000*	0.0000*	0.0000***	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Construction Year	0.0000**	0.0000	0.0000***	0.0000	-0.0000	0.0000	-0.0000	-0.0002	-0.0002	-0.0001	0.0000	0.0005***	0.0000	0.0001**	0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0002)	(0.0008)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
<u>Fixed effects</u>															
Postcode 4	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Transaction year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.0016	0.0251**	-0.0053	-0.0411	0.0428***	-0.0183	0.0100	0.3698	0.5434*	0.3078	-0.0595	-0.9199***	-0.0714	-0.0787	-0.2393
	(0.0177)	(0.0102)	(0.0177)	(0.2962)	(0.0148)	(0.0514)	(0.0149)	(0.6513)	(0.3189)	(1.5530)	(0.0669)	(0.1893)	(0.1185)	(0.0606)	(0.2268)
Observations	973,291	123,811	432,799	6,858	14,005	61,446	5,018	5,758	14,408	3,199	11,764	36,890	15,728	54,168	15,626
R-squared	0.0242	0.0211	0.0207	0.0218	0.0465	0.0139	0.1071	0.1188	0.1865	0.1486	0.0877	0.1235	0.0923	0.0878	0.0935