The External Effects of Shopping Center Openings on Residential Property Prices: Evidence from Budapest, Hungary

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Abstract

Shopping center openings have often been portrayed both as positive and negative events regarding their effect on surrounding house prices. This study investigates the external effects of shopping center openings on nearby residential property prices. Through a difference-in-difference method, it found that shopping center opening has a positive external effect on nearby property prices, indicating a 3.24% increase in property prices on streets near shopping centers after their opening, with a notable anticipation effect of a 0.74% annual increase as the opening approaches. The results further indicate that the average street-level prices increased four years after the opening. Lastly, these effects differ based on the size and the location of the shopping center. These findings suggest that shopping center developments positively affect local property markets, informing urban planning and real estate investment strategies.

Keywords: Difference-in-difference, external effects, shopping centers, event-study, house prices, opening, Budapest

Table of Contents

1. Introduction ... *6*

1.1 Motivation ... **6**

1.2 Academic relevance ... **6**

1.3 Research problem statement ... **10**

2. Theoretical and historical background & hypotheses ... *11*

2.1 Theoretical background ... **11**

2.1.1 External effects of shopping centers ... 11

2.1.2 Other factors in the externalities of shopping centers ... 13

2.2 Historical background of retail and shopping centers in Budapest ... **15**

2.3 Hypotheses ... **16**

3. Methodology & Data ... *17*

3.1 Methodology ... **17**

3.1.1 Difference-in-difference ... 17

3.1.2 Target area ... 19

3.1.3 Event study ... 20

3.1.4 Heterogeneity ... 21

3.1.5 Robustness check and assumptions tests ... 23

3.2 Data ... **25**

4. Results ... *27*

4.1 Difference-in-difference ... **27**

4.2 Event study ... **30**

4.3 Heterogeneity ... **32**

4.3.1 Heterogeneity based on the size of shopping centers ... 32

4.3.2 Heterogeneity based on the location of shopping centers ... 33

4.4 Robustness check ... **35**

5. Discussion ... *36*

5.1 Limitations ... **39**

5.2 Future research ... **39**

6. Conclusion ... *40*

7. References cited ... *40*

8. Appendices ... *49*

8.1 Appendix A: List of shopping centers ... **49**

8.2 Appendix B: Results from the target area determination ... **50**

8.3 Appendix C: Results of assumption testing ... **51**

8.4 Appendix D: STATA code ... **53**

8.5 Appendix E: Data management plan ... **70**

Preface

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1. Introduction

1.1 Motivation

The announcement of a new shopping center opening often receives both positive and negative coverage in media and public discourse. Frequently it is reported that the increased traffic, noise, crime, and air pollution will make the area surrounding the new shopping center less liveable (Beliczay, 1997; Filákovity, 2015; Negreira, 2021; Omeokachie, et al., 2023). Other outlets report on the increased access to amenities facilities and social gathering spaces provided by the new shopping center, highlighting its positive effects (Hercsel, 2021; Mooney, 2018; Pettersen, et al., 2023). Furthermore, the opening of new shopping centers has also become a city-planning issue, as it is often argued that it causes the closure of smaller, independent, high-street retailers, leading to the deterioration of inner cities, which has been extensively discussed in Hungary and elsewhere (Erkip & Ozuduru, 2015; Pál, 2023). Therefore, to investigate whether the positive external effects, such as the increased access to amenities facilities and social gathering spaces (Colwell, et al., 1985; Rosiers, et al., 1996; Sale, 2017; Wilhelmsson & Long, 2020; Zhang & Jin, 2023) outweigh the negative external effects, such as increased traffic, noise, crime, and air pollution, in relation to a shopping center opening (Beliczay, 1997; Shen, et al., 2020; Tse & Love, 2000), this study aims to use aggregate street level prices as a proxy to see whether there is an increased willingness to pay, to be close to a shopping center, and thereby derive its external effects (Barber, et al., 2021).

1.2 Academic relevance

Research into the impact of shopping centers on housing prices internationally has found that it has mostly contributed to increased housing prices, albeit at different rates due to different market characteristics (Sale, 2017; Wilhelmsson & Long, 2020; Zhang, et al., 2020; Zhang, et al., 2019). However these studies have been carried out outside Europe, such as in China (Zhang, et al., 2019; Zhang, et al., 2020), South Africa (Sale, 2017), the United States (Yu, et al., 2012) or Western Europe, such as in the Netherlands (Mingardo & van Meerkerk, 2012), or Sweden (Wilhelmsson & Long, 2020). Therefore, there is an existing gap within the literature which this study aims to address, as despite extensive research on urban development, the specific effects of shopping center openings on residential property prices in Budapest or in the wider CEE region remain underexplored.

Similar to other countries in the Central-Eastern European (CEE) region, Hungary has experienced an economic transition that continues to affect the real estate investment sector today. After the regime change in 1990, Hungary transitioned to a market economy from a previously socialist / communist economic model (Kovacs, et al., 2013; Sailer-Fliege, 1999). Wide-scale privatisation took place in land and real estate, among other sectors as well, which in 2004, further intensified due to Hungary's accession to the European Union, providing increased access for foreign investors to the Hungarian market (Kovacs, et al., 2013). Since then, Hungary has been the largest recipient of Foreign Direct Investment (FDI) within the CEE region, and more than half of the total FDI inflow to Hungary was received by Budapest and its metropolitan region (Adair, et al., 1999; Kovacs, 2009; Kulcsár & Brown, 2011). A similar trajectory of transition has been observed in other Eastern-European post-socialist / communist countries as well, such as in Slovenia, Slovakia, Czech Republic, and Poland (Turk, 2014). After the fall of socialism / communism, the blurry boundaries between economy and state and the weakness of democratic institutions have characterised transition economies throughout the CEE region (Nagy, 2005). The different political and economic structures stemming from the communist or socialist past and the subsequent transition, are still present in Eastern European countries through formal rules, such as laws and constitutions, informal rules such as practices, beliefs, and rules-of-thumb, property rights and local governance of land-use planning and development (King, 2011; Nozeman & Van der Vlist, 2014). These differences are reflected in the yields and rents of both the office and retail sectors, as cities such as Prague, Warsaw and Budapest, are characterised as a developing, often "exotic" locations of investment with high yields, compared to the major cities in Western Europe, such as London or Paris (Nozeman & Van der Vlist, 2014). Therefore, insights gained from this study will yield a broader understanding of real estate sector processes in the CEE region, with its differing institutional background and trajectory.

As investment into real estate as an alternative sector is growing, and Budapest is a key city in the CEE region, there is a need to understand the local real estate processes and its effects. Globally, there has been a tendency for growth in alternative assets, with more portfolios assigning a higher weight to alternatives (Loeffler, 2023; Wang, 2022). Prime yields in both retail and offices remain more than a percentage higher in the CEE region compared to Western

Europe, as well as the region experiencing a higher year-over-year growth in all real estate market segments (Almond, 2024). Budapest’s economic growth has been consistently higher than other major cities’ in the CEE region (Cushman&Wakefield, 2024). It was achieved through large employment sectors in finance, accounting, insurance, and business consultancy, as well as the opening of regional hubs by several large multinational corporations, such as the largest European office of BlackRock, BP or ExxonMobil, which have also attracted potential employees internationally to settle here, increasing the demand for residential development (Cushman&Wakefield, 2024; ExxonMobil, 2024; Forbes, 2018; Hungarian Investment Promotion Agency, 2019). Overall, Budapest has experienced the highest office employment in the CEE region since 2015, and this trend is expected to continue (Cushman&Wakefield, 2024). Therefore, the growing interest in real estate alternatives and Budapest provides the ideal basis for analysis, which can be later applied regionally.

Various processes of the real estate market have been studied across Budapest, however, there has been limited research on the effects of shopping centers among the determinants of house price changes. The retail sector has been mostly studied highlighting the transition period and subsequent changes. Retail activity has widened and grown, as disposable incomes and consumption grew (Horváth & Soóki-Tóth, 2014). International supermarket operators have made inwards into the country’s property market (Kok, 2007). There was an initial period of investing in an unknown territory for Western developers, leading to large speculation and oversupply issues in retail developments (Kok, 2007). During these years, the first wave of market-based shopping center developments opened in Hungary, mostly by large foreign companies and by a few from Hungary (Sikos & Hoffmann, 2004).

Determinants of changes in local housing prices in Budapest have also got limited research attention. From the few studies, Czinkan & Horváth (2019) has found that access to public transport links is a key determinant of an increase in housing prices. Beres, et al. (2019) found similar results when examining the effect of the newly established metro line (numbered 4) in Budapest. In areas in which there were limited public transport access before, the effect on real estate prices was significant, while in areas which were already had good transport connections, its effect was negligible (Beres, et al., 2019). Kutasi (2016) has also found similar results, meaning that while access to amenities and transport links is key in determining house price increase, inner city areas were more valuable. Kauko (2007) has also highlighted that, among the factors influencing housing location attractiveness in Budapest's inner city, the quality of houisng is a key attribute for buyers. Lastly, if the district where the house is located, has been viewed positively, and it is experiencing a population increase, it also had a strong positive impact on prices (Czinkan & Horváth, 2019). However, only limited research has addressed the impact of shopping centers on house prices in Budapest, or in Hungary in general. Other studies have examined the broader impacts of urban development in Eastern European contexts, such as the effects of infrastructure improvements and economic transitions on local economies and property values, underlying how these processes are unique in Eastern European urban contexts, highlighting how the opening of new shopping centers might show a similarly regionally specific dynamics (Buček, 2016; Gentile, et al., 2012).

Beyond addressing a gap in the literature, this study contributes to the current body of research through the unique combination of methods in the field of real estate. It combines the difference-in-difference with an event study, also looking at when the effect of property price increase is apparent, which has not been included in other studies employing a difference-in-difference methodology (Zhang, et al., 2019; van Duijn, et al., 2016). This approach allows for the exploration of the temporal dynamics of the external effects, beyond just examining the general effect after the opening. This will yield generalisable insights into the how and when the external effects become apparent, in the context of Budapest and the CEE region. Furthermore, hedonic regression price models are prone to omitted variable bias, not controlling for various factors which could influence property prices, mainly due to unobserved neighbourhood and housing characteristics, which may not be fully captured by the location fixed effects (Brooks & Tsolacos, 2010; Zhang, et al., 2019). However, by using street level aggregated data, this study controls for various neighbourhood characteristics which influence housing prices, such as public transport connections (Dubé, et al., 2014), as well as the closeness and amount of green space in the vicinity (Jiansheng, et al., 2014).

Therefore, this study will provide key insights into the effects of the real estate market process in a key city in the CEE region, at a time when alternatives are of growing interest to investors, highlighting how the external effects of shopping center openings may have a regionally specific dynamic. Furthermore, it aids in the understanding of these external effects by employing a unique set of methods next difference-indifference.

1.3 Research problem statement

The research aims to investigate the external effects of shopping center openings. The study will employ street level aggregate housing prices as a proxy to measure the external effects. It will employ a difference-in-difference methodology to measure the extent of the external effects, similarly as found in existing ligature, using a target and control areas (Ahlfeldt, et al., 2016; Zhang, et al., 2019; van Duijn, et al., 2016). It will further investigate whether there is an anticipation effect leading up to the opening of a shopping center (Colwell, et al., 1985). Then, it will investigate using an event study, that how many years after the opening of a shopping center are the external effects observable in the target area. Lastly, it will investigate whether there is any heterogeneity in terms of the external effects based on the size of the shopping center and its location. Therefore, the central research question is:

"To what extent does the opening of a shopping center affect the surrounding housing prices in Budapest?".

To understand not just the external effects after the opening, but also explore its temporal dynamics, sub-question 1 is formulated as:

"How many years after the opening of a shopping center is the effect observable?".

Lastly, there could be differences based on the size and location of the shopping center. Larger shopping centers may generate larger external effects on nearby property prices, due to more anchor tenants, a more diverse tenant mix, and by having more leisure focused facilities (Teller & Reutterer, 2008; Zhang, et al., 2019; Zhang, et al., 2020). Furthermore, there is a duality on Budapest's two sides along the Danube, Buda and Pest, in terms of terrain, topography, history, socioeconomic characteristics, and public transport which can influence the degree of external effects as well (Horváth & Soóki-Tóth, 2014; Jang & Kang, 2015). Therefore, sub-question 2 is:

"Are there differences in terms of the effect based on the size and location of the shopping center?"

The structure of the remaining sections in this paper is outlined as follows: it will first provide an overview of relevant literature and formulate the hypotheses related to the research questions. It will then elaborate on the data and methods used. Furthermore, it will present and discuss the analysis's findings, as well as provide a robustness check. Lastly, it will conclude and highlight limitations and avenues for future research.

2. Theoretical and historical background & hypotheses

This section provides an overview of the theoretical and historical frameworks and concepts that underpin the study. It includes a review of relevant literature on retail and shopping centers, the external effects of shopping centers, and other influencing factors. Therefore, the theoretical background section will elaborate on the literature on external effects of shopping centers and examine factors that influence the degree of external effects of shopping centers. Then the historical background section will provide an overview on Hungarian retail and its development in Budapest. Lastly, the hypotheses are then formulated based on this theoretical foundation.

2.1 Theoretical background

Externalities arise when the use of a parcel of land affects neighbouring properties and causes a change in their values (Do, et al., 1994). In the case of shopping center openings, as they are multi-functional, it can arise due to better access to shopping amenities, or alternatively, the other functions that a shopping center provides, such as entertainment and leisure (Zhang, et al., 2020). Furthermore, the change in land use by opening a shopping center could also generate externalities beyond the amenities and functions it provides, such as for example by funding the redevelopment of the area surrounding it (Ahlfeldt, et al., 2016). These externalities derived from the place-based investment can be higher even if the area where the shopping center is built is a brownfield, as it is the case with most shopping centers in Budapest (Kiel & Zabel, 2001; Sikos & Hoffmann, 2004).

2.1.1 External effects of shopping centers

Shopping centers act as a focal point of retail activity, which emerged as the result of retail agglomeration, stemming from the utility maximization behaviour of customers (Hotelling, 1929; Larsen, et al., 2015). Shopping centers provide residents living in their vicinity or surrounding neighbourhood better access to amenities, such as shopping, entertainment, and leisure facilities, which increases the attractiveness of the area around the shopping center (Bloch , et al., 1994; Kuang, 2017).

The external effects of shopping centers on residential property prices have long been an interest to researchers. Colwell, et al. (1985) first studied the effects of proximity to a shopping center before and after its announcement and opening in Urbana, Illinois, in the United States. It found that shopping centers had positive effects on surrounding housing prices, however at different distances. If the property was located closer than 1500 feet (457.2 meters), negative externalities were apparent, but for properties located beyond 1500 feet of the shopping center, positive externalities were apparent (Colwell, et al., 1985). The negative effects within the 1500 feet radius can be attributed to externalities such as noise, pollution and traffic congestion (Colwell, et al., 1985). Later, Sirpal (1994) also found a similar effect of distance in Florida, so that there is a radius where house prices are lower due to the negative externalities and then rise, until reaching a reach maximum and then falling again. Rosiers, et al. (1996) also investigated the effect of shopping centers on surrounding residential prices in Quebec, Canada, finding that prices are 5% higher within a 200–300-meter ring around the shopping center, but then fall rapidly. Zhang, et al. (2019) found that in Hangzhou, China, property prices increased by 10% after the opening of the West Intime shopping center. Zhang, et al. (2019) has further found the positive effects to be most pronounced in the first two years after the opening of the shopping center and diminish over time as the study period got further from the opening date. Yu, et al. (2012) found that there is an increase of 2.5% - 3.0% in sales prices of housing if the property is located within the 3–10 minutes driving-time buffer around Turkey Creek Shopping Center, in Knoxville, USA. Kholdy, et al. (2014) found that there is a positive effect on housing prices of shopping centers in the area between 1.3 – 3 miles (2092 - 4828 meters) radius in Victoria Garden, California, USA. Wilhelmsson & Long (2020) found in Stockholm examining 39 shopping centers, that within a one-kilometer radius, shopping centers have a positive effect on housing prices, with the effect being even more pronounced when the distance is only 400 meters, resulting in a 1.6% increase (Wilhelmsson & Long, 2020). Similar findings of the positive effects of shopping center openings on house prices have been confirmed by a wide range of studies since, such as by Sale (2017) in South Africa, Pope & Pope (2015) in the US, Kurvinen & Wiley (2019) in Finland, Zhang & Jin (2023) in China and Tuaire, et al. (2023) in Namibia.

Regarding the temporal patterns of the external effects, there is some evidence of anticipation effects. Colwell, et al. (1985) found that house prices started to increase already after the announcement of the opening of the shopping center, not just after the opening. Zhang, et al. (2019) did not find any anticipation effect before the opening in terms of housing price increase, but an increased number of transactions and new construction starts in the vicinity of the shopping center after the announcement of the opening. Zhang, et al. (2019), also found that prices are the highest until 2 years after the opening and then it decays. Therefore, there is evidence of anticipation effects, as permits and construction can take many years and external effects are the strongest right after the opening (DiPasquale & Wheaton, 1992).

Still, while a demonstrated wide body of literature supports that house prices increase in the vicinity and after the opening of a shopping center, some studies are highlighting that negative externalities outweigh positive externalities in certain urban contexts. Negative externalities stem from higher traffic congestion, noise, nuisance, air pollution drug use, and crime (Dúll, et al., 2006; Kahn & Schwartz, 2008; Lens & Meltzer, 2016). In Hong Kong, Tse & Love (2000) found that house prices increase as distance from the shopping centre increases. Similarly, Shen, et al. (2020) found the same effect in Shenzhen, China. Therefore, increased housing prices as a proxy for external effects after the opening of a shopping center, can only manifest if the positive external effects outweigh the negative external effects in the given urban context.

2.1.2 Other factors in the externalities of shopping centers

The size and type of shopping centers significantly influence their external effects. Shopping centers provide external effects beyond just shopping access, they are increasingly becoming spaces of leisure, thereby having greater importance in the general urban recreational lifestyle (Fasli, et al., 2016). They also act as social gathering spaces, where people meet for a meal or coffee, as well as a space where people can congregate and meet friends (Dúll, et al., 2006; Fasli, et al., 2016). Various other amenities within a shopping center, such as a cinema can also increase its attractiveness and power to draw in customers (Ooi & Sim, 2007). Erkip (2005) has found that only half of all the people who go to the shopping center are strictly going for shopping, while the other half is going for other activities and browsing. Zhang, et al. (2020) also found that shopping centers which contain many accessible leisure facilities, have a greater appeal to residents in the area. These trends have been also noticed by developers, who are trying to reframe the shopping center experience from shopping towards a leisure activity (Howard, 2007). Therefore, the external effects provided by a shopping center for its residents in the surrounding area is not limited to shopping amenities, but as spaces of leisure and social gathering.

Larger shopping centers could attract more anchor tenants, more diverse tenant mix, have more leisure focused facilities and provide more parking and thereby derive larger external effects. Teller & Reutterer (2008) show that the appropriate tenant mix, which can provide merchandise of good value in the eyes of the customers is extremely important in determining the attractiveness of shopping centers, as well as the presence of anchor tenants. Furthermore, it is also key that the general environment and atmosphere of the shopping center is of high quality and valued by customers (Ruiz, et al., 2004). Similarly, Sirmans & Guidry (1993) studied the market rents for shopping centers and found that larger shopping centers as well as, well-chosen anchor tenants have a positive impact on customer drawing power and therefore rents. These findings have been confirmed by Zhang, et al. (2020), as the kind of facilities and shops the shopping center provides also had a large impact on customer drawing power. Sirpal (1994), in his analysis, also found that the positive effect on house prices of larger shopping centers is higher than that of smaller shopping centers by 5%. Jang & Kang (2015) also found that it is not only the size of the shopping center, but the type of retail tenants which can influence the effect on housing prices. Furthermore, this effect varied based on which area of the city was observed (Jang & Kang, 2015). The higher availability of parking, which is often available in larger shopping centers, also generates higher turnover (Mingardo & van Meerkerk, 2012). Therefore, as larger shopping centers, due to the higher number of anchor tenants, more leisure focused facilities, and parking, could exhibit larger external effects than smaller shopping centers. Furthermore, the location of the shopping center also influences its degree of external effects. Therefore, the impact varies based on the location and size of the shopping centers, leading to the hypothesis that larger centers in well-connected areas have more pronounced effects (Zhang, et al., 2020).

2.2 Historical background of retail and shopping centers in Budapest

Budapest has experienced a distinct trajectory of retail and shopping center development, influencing the external effects generated. The political and economic transition in 1990 had a substantial impact on the economic restructuring of Hungary, and thereby its policy on real estate and urban development, as the market economy emerged from central planning (Kovacs, et al., 2013; Sailer-Fliege, 1999). Local municipalities have expanded jurisdiction on urban policy and planning. In Budapest, a central city authority was established, as well as 23 districts (they are noted with Roman numerals or numbers), which each hold most of the decision-making authority on urban policy and planning issues within their districts (Kovacs, et al., 2015). The districts formulate their local development strategies and facilitate the dialogue with real estate developers regarding redevelopment opportunities within the districts (Kovacs, et al., 2013). A key issue was the redevelopment of brownfields, which have emerged from former rail network areas or due to the sudden deindustrialisation (Dannert & Pirisi, 2017; Kukely, et al., 2006; Kunc, et al., 2014). The large majority of shopping centers were built on brownfields in Budapest, which has also contributed to the overall redevelopment of the surrounding areas through large-scale inner city rehabilitation programs, developing or extending pedestrian areas and main squares (Horváth & Soóki-Tóth, 2014; Sikos & Hoffmann, 2004). These can exacerbate the positive external effects, as shopping centers and retail facilities which are well integrated into the urban fabric, and are easily accessible by public transport and foot as well, generally exhibit stronger positive externalities on housing prices (Jang & Kang, 2015; Song & Sohn, 2007).

Shopping centers were first built in Budapest during socialism / communism, the 1970s, were relatively small, less than 20,000 m^2, and provided only a few parking spaces (Sikos & Hoffmann, 2004). Then from 1980–1994, there were several new shopping center developments, which were larger and more modern (Sikos & Hoffmann, 2004). However, especially from 1995, there was a major increase in both the number and size of constructed shopping centers (Horváth & Soóki-Tóth, 2014; Sikos & Hoffmann, 2004). After the economic transition, state-owned retail chains were privatized and a wide range of retailers entered the market, suddenly increasing the demand for modern retail space (Horváth & Soóki-Tóth, 2014). There was no real estate investment market prior to 1999 as there was a very limited number of buildings, built during socialism / communism, that met the requirements of institutional investors (Horváth & Soóki-Tóth, 2014). The ascension to the EU in 2004, gave a large stimulus to real estate investments and the retail sector observed an increasing retail turnover, which furthered the scale and number of new shopping center developments due to increased globalisation and the linking of cities' real estate markets into international investment (Adair, et al., 1999; Horváth & Soóki-Tóth, 2014; Sigler & Wachsmuth, 2016). This is the period and environment when the shopping centers of this study were opened, between 2005 and 2022. Therefore, Budapest has experienced a substantial change in its economic, urban, and retail landscape, influencing the trajectory of shopping center developments and their external effects.

2.3 Hypotheses

Based on the existing literature in relation to the research questions and the aim of this study, while there is some literature highlighting the negative external effects of shopping center openings observed through housing prices, overwhelmingly shopping center openings induce positive external effects in terms of house price increases in the surrounding areas. These external effects can stem from the shopping center's retail amenities, as well as leisure and other entertainment facilities. Lastly, shopping centers built well-connected within the urban landscape can also exhibit positive external effects based on the improved land use and surrounding public space. Therefore, the hypotheses formulated for the research questions are as follows:

H1: The opening of a shopping center will exhibit positive external effects on surrounding housing prices.

H2: The positive external effects will be exhibited right after the opening of the shopping center, rather than several years after, as highlighted by previous studies.

H3: As highlighted in previous studies, there will be differences in the external effect based on the size and location of the shopping centers.

3. Methodology & Data

3.1 Methodology

To identify the external effects of shopping center openings, aggregate street level property prices are observed before and after a shopping center opens. To disentangle the external effects of shopping center opening indirectly, residential property prices are used as a proxy and observed in areas that received external effects, defined as target areas and those that did not, defined as control areas. The method to define the target and control areas is elaborated on later.

3.1.1 Difference-in-difference

To identify the external effects of shopping centers openings on average street level prices, a difference-in-difference model is estimated to effectively capture the causal impact of shopping center openings on property prices by capturing the price change after openings in predefined treated (target) and untreated (control) areas. This approach helps to isolate the effect of shopping centers by controlling for unobserved variables. Specifically, the following equation is estimated:

$$\begin{aligned}\ln\left(P_{ijt}\right) = \; & \alpha + \beta_1 \, Target_i + \beta_2 \, Post_t + \beta_3 \, (Target_i \times Post_t) + \beta_4 \, Trend_t \\ & + \gamma_t + \mu_j + \varepsilon_{it}\end{aligned} \tag{1}$$

where $log\ (P_{ijt})$ is the log of the average price a given street i, in geographical area j, and in year t. The average price on a given street is log transformed, as prices are typically skewed (Appendix A). $Target_i$ is a dummy variable indicating whether street i is located in the target area or not. $Post_t$ is a dummy variable indicating whether the price for street i is measured after the opening of the closest shopping center or not. $Trend_t$ denotes the time to the nearest shopping center opening in years, until the year of shopping center opening and takes the value of zero after the opening. γ_t denotes the year fixed effects, between 2005 and 2022. μ_j denotes the location fixed effects of districts in Budapest. ε_{it} is an idiosyncratic error term. It should be noted that the $Post$ dummy is only interpreted when the time fixed effects are not included, as in Model 1 and it is excluded in all other models, where time fixed effects are included as in Model 2, 3, 4.

The key variables of interest are $Target$ and $(Target * Post)$. These variables provide key insights into the external housing market effects of the shopping center opening. $Target$ equals one if property i is in the target area, zero otherwise. It captures the difference in average street level prices between streets located in the target area and those in the control area. $(Target * Post)$ is the main variable of interest, equalling one if street i is located in the target area and measured after the opening of a shopping center, zero otherwise. The coefficient of this variable measures the external effect of the opening of shopping centers on average street level prices in the target area. The coefficient of $Trend$ measures the anticipation effects of the opening of shopping enter, as it would be known in most cases already before the opening due to the years of construction. It takes the value zero after the opening of the shopping center to isolate the effect of anticipation leading up to the opening. While many studies, such as Sale (2017), Schwartz, et al. (2006), Wilhelmsson & Long (2020), Zhang, et al. (2019), Zhang, et al. (2019), Zhang, et al. (2020), van Duijn, et al. (2016) include a distance variable in the model, due to the data structure of street level observations, and placing the coordinates in the middle of streets, the distance would not yield insights in the scope of this paper.

Four models are estimated. In the first model, the main variables of interest: $Post$, $Target$ and $(Target * Post)$ are estimated, without the time fixed effects, to understand the coefficient for the Post variable, which would otherwise interfere with the time fixed effects. In the second model, time fixed effects are included and $Post$ is excluded. In the third model, the $Trend$ variable is added to observe the anticipation effects of shopping center openings. Lastly, in the fourth model, street level fixed effects are added as well to account for unobserved heterogeneity across each individual street and to control for the fixed characteristics of each street (Bell & Jones, 2014). In this model, the variable $Target$ and the location fixed effects are omitted, as they would be collinear with the street level fixed effects.

While most studies related to housing and real estate, rely on cross-sectional, transaction data, such as Wilhelmsson & Long (2020), Zhang, et al. (2019), Zhang, et al. (2019) and Zhang, et al. (2020), panel data has been also widely employed in other areas of research using difference-in-difference methodology, such as in economics Callaway & Li (2019), policy evaluation Beatty & Tuttle (2015), finance Berger & Roman (2020), Conti (2014), education Schwerdt & Woessmann (2020) and health related studies (Yamamura & Tsutsui, 2020). To account for the panel data structure, standard errors are clustered on street level (Abadie, et al., 2023).

3.1.2 Target area

To determine the target areas for the difference-in-difference model, an alternative specification is estimated to allow for the data to indicate the reach of external effects and their decay by distance, in a nonparametric way, similarly to approaches used by (Ahlfeldt, et al., 2016; van Duijn, et al., 2016). Specifically, the following equation is estimated:

$$\ln\left(P_{ijt}\right) = \alpha + \beta_2 \, Post_t + \textstyle\sum_{S=1}^{S} \beta_S \, R_{its} + \gamma_t + \mu_j + \varepsilon_{it} \tag{2}$$

where $log\ (P_{ijt})$ is the log of the average price of a given street i, in geographical area j and in year t. $Post_t$ is a dummy variable indicating whether the price for street i is measured after the opening of the closest shopping center or not. γ_t denotes the year fixed effects, between 2005 and 2022. μ_j denotes the location fixed effects by districts in Budapest. ε_{it} is an idiosyncratic error term. R_{its} is a vector of ring variables, based on the location of street i, in year t. It denotes a set of dummy variables which take the value of one if the street is located within 250 m rings (0–250, 250–500, 500–750, 750–1000, 1250-1500, 1750-2000, 2000-2250, 2250-2500 m) and 500 m rings (2500-3000, 3000-3500, 3500-4000, 4000-4500, 4500-5000 m) around the closest opened shopping center, and zero otherwise. The 5000 meters limit is chosen as most streets are located within this distance to the closest opened shopping center (Appendix A). Based on the results of equation 2, the target area was determined to be (750 meters) and a control area between 750 and 1500 meters to the nearest opened shopping center. The results from the target area determination can be found in Appendix B. A similar approach using outer rings is often employed in literature (Ahlfeldt, et al., 2016; Schwartz, et al., 2006; Zhang, et al., 2019; van Duijn, et al., 2016). Then, all streets which are beyond the control area were dropped. Furthermore, all the streets which are overlapping between the different shopping centers in their target and control area were dropped as well. This ensures that the estimators remain unbiased and there are no streets taken as duplicates in the estimates. After the determination of the target area and deletion of overlapping streets, 233 streets remain in the dataset. The descriptive summary table of the target and control area can be found in Table 1.

Descriptive summary table for target and control areas

Target area

VARIABLES	Unit	Observations	Mean	Std. Dev.	Min	Max
Average Street Price	1000 HUF	1,134	404.6685	231.7136	121.1960	1418.0000
Log of Average Street Price	1000 HUF	1,134	5.8576	0.5280	4.7974	7.2570
Distance	Meter	1,134	514.5241	134.9066	174.8918	746.9868
Time to Shoping Center Opening	Year	1,134	1.9762	6.3442	-16	15.0000

Control area

VARIABLES	Unit	Observations	Mean	Std. Dev.	Min	Max
Average Street Price	1000 HUF	3,060	405.7471	234.3523	111.2715	1610.0000
Log of Average Street Price	1000 HUF	3,060	5.8575	0.5352	4.7120	7.3840
Distance	Meter	3,060	1131.7800	218.7903	753.1467	1498.7990
Time to Shoping Center Opening	Year	3,060	2.1176	5.8671	-16	15.0000

Table 1: data descriptive summary table for target and control areas

3.1.3 Event study

To further investigate the external effects of shopping center openings, an event study is employed within the target area to determine whether the effect of opening is observed over time. This allows to observe the external effects, uncovered through the difference-in-difference method, over time and provide a more granular view. Event studies have been widely used in finance research (Corrado, 2011; Shah & Arora, 2014), but more recently, they have been employed in difference-in-difference analysis as well, especially in the case of heterogenous treatment effects (Clarke & Schythe, 2020). The following model is estimated within the target area:

$$y_{gt} = \alpha + \sum_{j=2}^{J} \beta_j \,(Lag\ j)_{gt} + \sum_{k=1}^{K} \gamma_k \,(Lead\ k)_{gt} + \gamma_t + \varepsilon_{it} \qquad (3)$$

where y_{gt} is a panel consisting of g streets and t time periods in years between 2005 and 2022. Lags and leads are binary variables indicating that the given street was a given number of periods away from the event shopping center opening in that time-period. γ_t denotes the year fixed effects, between 2005 and 2022. ε_{it} is an idiosyncratic error term. The location fixed effects are excluded, as they would be collinear with the street level fixed effects. The model uses one year before the event as the baseline. Two models are estimated. The first where the leads and lags are accumulated beyond a point where only very few units received treatment, to avoid under-identification, which occurs when there are not enough data points to estimate the effects reliably (Schmidheiny & Siegloch, 2019). In the second model, all leads and lags are estimated, providing detailed information about the effect for each year. This structure is also why standard errors are only clustered in Model 1, as in Model 2, in certain years there are not enough units receiving treatment to use clustered standard errors, therefore robust standard error specification is used. The key variables of interest in this model will be the significance of the $Lead$ variable and their sign, which will point to whether, and when an increase in street level prices can be observed the target area after the shopping center opening.

3.1.4 Heterogeneity

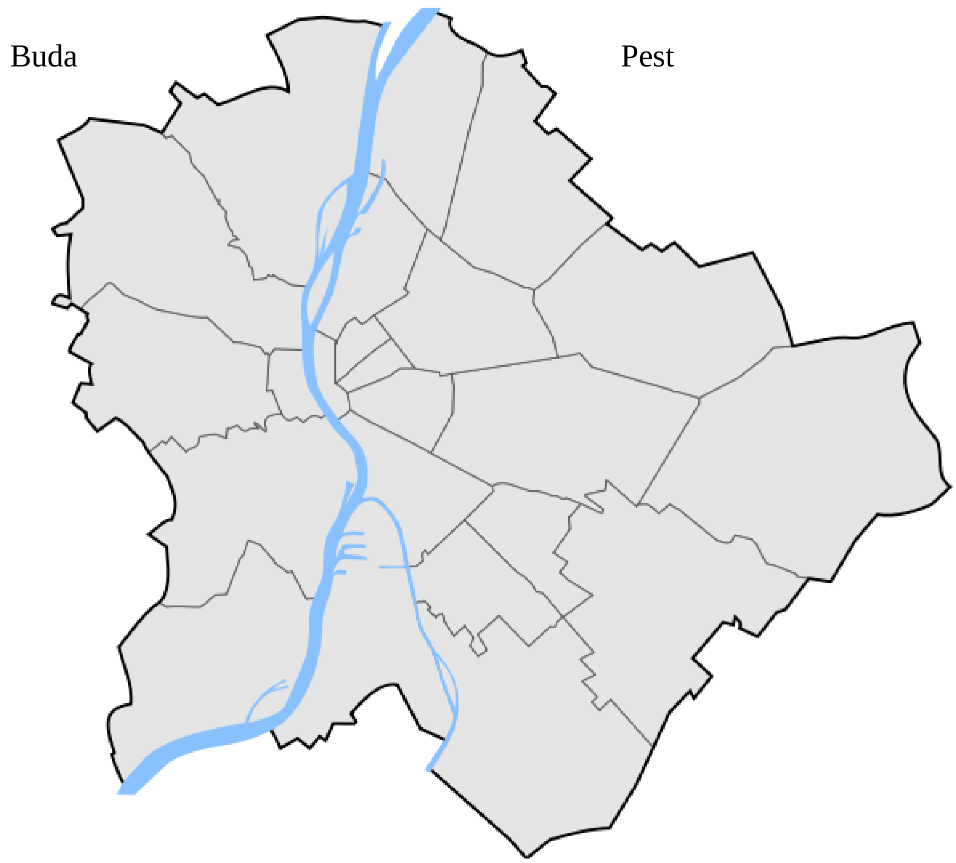
To test the heterogeneity in the external effects of opened shopping centers a Chow-test has been employed, based on the specification of (Brooks & Tsolacos, 2010). The Chow-test is a statistical test that is used to determine whether there is a structural break or heterogeneity in the coefficients of a regression model, similarly to an F-test (Brooks & Tsolacos, 2010). It involves dividing the data into two sub-groups and comparing the regression coefficients of each sub-group. The Chow-test statistic is given by the formula:

$$Chow\ test\ statistic = \frac{(RSS\ -\ (RSS\,1\ +\ RSS\,2))}{(RSS\,1\ +\ RSS\,2)} * \frac{T - (m * k)}{(m * k) - k}$$

where RSS1 represents the sum of squared residuals from the first sub-group of the data, RSS2 is the sum of squared residuals from the second sub-group of the data, RSS is the sum of squared residuals from the pooled regression with all the data, k denotes the number of independent variables in the regression, m denotes the number of sub-groups and T signifies the sample size.

The Chow-test has been conducted based on both the size and the location of shopping centers. First, regarding the size of shopping centers, there is a high variation present, ranging from

6,000 square-meters to 72,000 square-meters. The reason behind this is that larger shopping centers may generate larger external effects on nearby property prices as elaborated above and possibly a larger catchment area as well (Teller & Reutterer, 2008; Zhang, et al., 2019). The chow tests performed based on the two regressions and it was possible to determine whether the regressions were different, when the two groups were separated or not.



Picture 1: indicating the Buda and Pest side and showing the Danube River (with blue), source: https://www.futas.net/terkep/budapest/kepek/budapest-keruletei-terkep.png.

Budapest is a city located along the Danube River, with the river's Eastern bank being Buda and the Western bank being Pest, as shown in Picture 1. Due to its topography, Buda is often referred to as Buda Hills, while Pest lies in a flat area. Buda has a panoramic greenbelt, which has developed into an elite residential area, even though it is harder to access to the city centre (Horváth & Soóki-Tóth, 2014). The duality of the two sides, stemming from the different terrain, topography, and history is reflected by the housing prices, which have been accredited both by industry research Eltinga (2023) and academic research as well (Horváth & Soóki-Tóth, 2014). Therefore, the heterogeneity test will be able to investigate if these differing house price characteristics will exhibit themselves in the external effects, as the housing market processes and characteristics are markedly different on the two sides (Cushman&Wakefield, 2024; Eltinga, 2023). Furthermore, such differences are also apparent in the liveability, sentiment and valuation of prefabricated communist / socialist housing estates (Balla, et al., 2017; Kutasi & Badics, 2016).

3.1.5 Robustness check and assumptions tests

To ensure the validity and reliability of the results, it was ensured that the models satisfy the assumptions of a regression, based on the specification of (Brooks & Tsolacos, 2010). An assumption of the error term, namely that the average value for the error terms is zero, is eliminated as a possible issue by including a constant in all models. The correlation matrix can be found in Appendix A. There are no serial correlations observed which would disrupt the model, as the high correlations are only present between the average street price and its log-transformed form, as well as the $Post$ and $Trend$ variables with the time to shopping center opening, however, they are closely related, so it is expected. The VIF tables for models can be found in Appendix A, and there are no values which are too high, disrupting the models. The residuals are also normally distributed for all models, as indicated by the histograms in Appendix A. To account for the panel data structure, standard errors are clustered on street level (Abadie, et al., 2023). Clustered standard errors further account for possible serial autocorrelation and are robust to heteroscedasticity (Moody & Marvell, 2020).

There has been recent literature highlighting that the traditional difference-in-difference (also referred to as two-way fixed effects) estimates may be biased in the case of dynamic or staggered difference-in-difference models where the treatment heterogenous, so it is not adopted at the same time by all the treated groups (Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). Goodman-Bacon (2021) shows through the difference-in-difference decomposition theorem, that the two-way fixed effects estimator equals the weighted average of all possible two-group and two-period difference-in-difference estimators in the case of dynamic or staggered treatment effects. Therefore, this study will employ the "Bacon decomposition" in STATA ("estat bdecomp") to check for the validity of the coefficients, looking at the weight of the overall coefficient stemming from being treated or untreated.

Furthermore, the heterogenous treatment effect complicates whether a key assumption of the traditional difference-in-difference methodology, referred to as parallel trends is satisfied. It highlights that the outcomes in average street level prices, the dependent variable, between the target and control area before the shopping center opening should be identical (Ryan, et al., 2018). As shopping centers are opened at different times, this assumption is tested by plotting the average street level prices of target and control areas before and after the shopping center openings (Zhang, et al., 2019) (Appendix C). As the trend in both target and control areas follow similar patterns, it ensures that the parallel trend assumption is satisfied (Zhang, et al., 2019).

Additionally, as a robustness check of the results from Equation 1, a model using first differences is estimated, examining the effect of shopping center opening. It should be noted that this model is only estimated to confirm the results from the Equation 1 and does not interfere in the interpretation of the main results of this study. Specifically, the following model is estimated:

$$\Delta_t \ln(P_{ij}) = \alpha + \beta_1 \, Post_t + \beta_2 \, (Target_i \times Post_t) + \mu_j + \varepsilon_{it} \qquad (4)$$

Where $\Delta_t$represents the difference between the log of the average street level price of a given street i, in geographical area j, in year t and the log of the average street level price of the same street in year t-1. $Post_t$ is a dummy variable indicating whether the price for street i is measured after the opening of the closest shopping center or not. μ_j denotes the location fixed effects of districts in Budapest. ε_{it} is an idiosyncratic error term. Year fixed effects are excluded from this model, as they would be interfering with the coefficient of the $Post$ variable. In the first estimated Model with the above specification both the target and control areas are included to check the robustness of the ($Target * Post$) variable. In the second specification, only the target area is examined, looking at the $Post$ variable, which indicates the average street level price increase after a shopping center opens.

3.2 Data

The database utilized is called “Ingatlanadattár” meaning, Property Data Store, provided by the Hungarian Central Statistical Office (KSH) (Hungarian Central Statistical Office (KSH), 2023). It is based on the reported housing market transactions collected by the National Tax and Customs Administration (NAV); therefore, the data is robust and reliable (realista.hu, 2023). Furthermore, while ethical considerations arise as the value of individuals’ transactions are shared with the Statistical Office, it stipulates that the NAV only provides the values, and shares no personal information during these data transfers, therefore ensuring anonymity (Hungarian Central Statistical Office (KSH), 2023). The data is collected on a street level, and it reports on the district in Budapest and the street name, as there could be several streets with the same name in different districts. It provides the number of transactions per street, and then aggregates all the transactions on a given street and calculates an average price per square meter in HUF. The data differentiates between three housing types in Budapest: family / detached houses, apartments, and “panel”, referring to the prefabricated high-rise housing estates, which were mass-produced during the communist / socialist era. These are then aggregated to give the average square meter price for the given street. The data is available from 2005 until 2022.

Data cleaning was carried out in relation to the database’s structure. Due to the database’s collection method, the number of streets across the years from 2005 until 2022 is not constant. It fluctuates based on whether there was a transaction in the given year for the given street or not. Therefore, while in some years there is information on over 2500 streets, there are others when there are less than 1900 streets reported in the dataset. Therefore, the data was aggregated so that each street was deleted if there was a year missing the average street level price information for the given year, leaving 820 streets across the 23 districts in Budapest, for which the data was available from 2005 until 2022, creating a strongly balanced panel. The descriptive summary table for the data before the target and control area determination can be found in Table 2. Then the location (latitude and longitude) of each street was determined using the Geographic Information System (GIS), with the specification of determining the coordinates within the middle of the street for each street in the given district. This is important as there could be a street spanning over several districts.

Descriptive summary table

VARIABLES	Unit	Observations	Mean	Std. Dev.	Min	Max
Average Street Price	1000 HUF	14,760	383.0728	224.0844	97.2943	2003.0000
Log of Average Street Price	1000 HUF	14,760	5.8002	0.5310	4.5777	7.6024
Distance	Meter	14,760	3106.7480	2701.7270	113.2713	12001.7800
Time to Shoping Mall Opening	Year	14,760	2.0854	6.1320	-16	15.0000

Table 2: data descriptive summary table

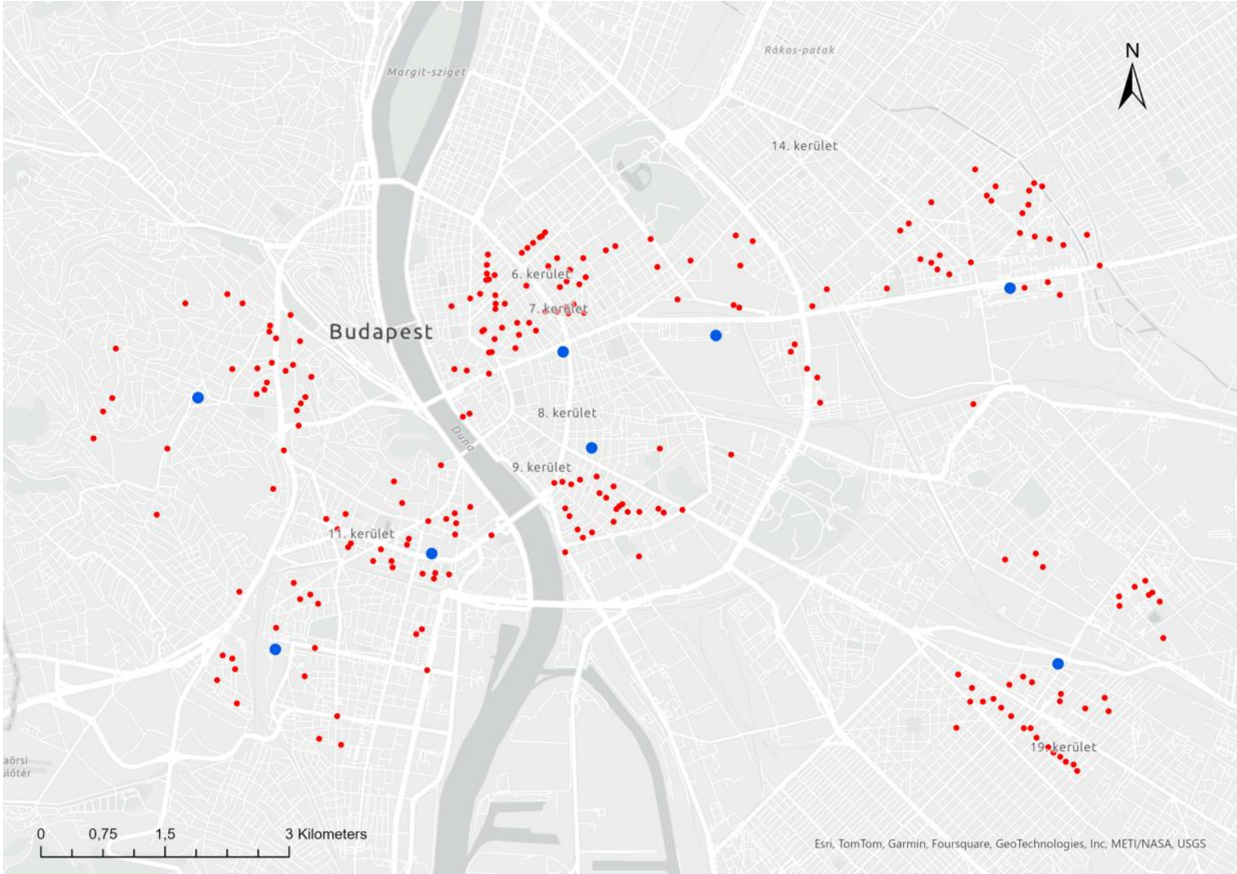
According to the MBSZ (Hungarian Council of Shopping Centers , 2023), there are 39 shopping centers in Budapest, however according to Cushman&Wakefield (2024) there are only 22, as many of the MBSZ's list there are shopping centers, which are focused mainly around one large retailer, such as Tesco, Aldi, Lidl or Jysk and a few small shops within their premises (Cushman&Wakefield Research, 2024). Cushman&Wakefield Research (2024) considers an appropriate tenant mix and quality of the shopping center premises as well, which provides a more substantial basis for the analysis. From the 22 shopping centers, only 9 have been opened between 2005 and 2022, the study period of this paper: Arena Mall, Allee Shopping Mall, Corvin Plaza, KOKI Terminal, Europeum, Hegyvidek Bevasarlokozpont, Arkad Budapest II, Balna Budapest and Etele Plaza. However, only 8 are continuously used a shopping center since, as Balna Budapest was bought by the Hungarian Tourism Agency (MTU) and used for exhibitions and other uses since, therefore it was excluded (Csurgó, 2019). In the final analysis only 8 shopping centers were included, which can be found in Table 3. The longitude and latitude of the shopping center were determined by their Google Maps addresses. The distance of each street to the nearest shopping center was calculated using the "geonear" function in STATA, using Euclidian or "crow" distance.

Shopping Centers

Shopping Center Name	Opening year	Size (GLA, sqm)
Arena Mall	2007	68,000
Allee Shopping Mall	2009	46,700
Corvin Plaza	2010	34,600
KOKI Terminal	2011	72,000
Europeum	2011	6,000
Hegyvidek Bevasarlokozpont	2012	6,000
Arkad Budapest II	2013	20,000
Etele Plaza	2021	55,000

Table 3: list of shopping centers included in the study

The investigated streets in the dataset are shown on the GIS map (Map 1) (with red), as well as the location of the shopping centers (with blue).



Map 1: location of streets (with red) and shopping centers (with blue)

Lastly, it is important that the researcher recognises their own positionality and possible biases as a long-time resident of Hungary and Budapest, which could influence the data collection and research process (Flowerdew & Martin, 2005). However, as the data is publicly available, as stated above, and the collection and research process are transparently described and reproducible, this ensures that the research remains unbiased for this study.

4. Results

4.1 Difference-in-difference

All calculations were carried out using STATA version 18. The exact percentage effect on sale price was calculated as: 100*(exp(beta)-1), due to the log-linear relationship, based on the specifications of (Brooks & Tsolacos, 2010). The results for all the difference-in-difference model specification can be found in Table 4. Model 1 has a R-squared value of 0.3467, meaning that the model explains 34.67% of the variance in the dataset. The F test indicates that the model results are significant, the low p-value strongly rejects the null hypothesis that none of the independent variables are related to the dependent variable. The results from Model 1 indicate that Post has a strong positive coefficient without the time fixed effects, meaning that average street level prices are 66.35% higher after the opening of shopping centers. This effect is significant on the 99^{th} percentile level. The coefficients for Target and Target*Post not significant at any level.

In Model 2, when time fixed effects are added and the variable Post is excluded, due to the interference, the R-squared value increases to 0.8907, meaning that the model explains 89.07% of the variance in the dataset. The F test also indicates that the model results are highly significant. The coefficient Target becomes significant on the 90^{th} percentile level, meaning that average street level price if a street is located in the target area is 5.87% lower compared to the control area. The coefficient for Target*Post is strong and positive, being significant on the 99^{th} percentile level. It indicates that the average street level price on street located within the target area and observed after the opening of a shopping center are 9.85% higher compared to the control area.

In Model 3, the variable Trend is introduced. The R-squared value is 0.8966, meaning that the model explains 89.66% of the variance in the dataset. The F test also indicates that the model results are highly significant. The coefficient Target is not significant at any level. The coefficient for Trend is positive, and significant on the 99th percentile level. It shows that as the opening of the shopping center approaches, the average street level prices are increasing by 2.23% in both the target and control areas. The coefficient for Target*Post is slightly weaker but still positive. It shows that the average street level price on streets located within the target area and observed after the opening of a shopping center is 5.36% higher compared to the control area. This effect is significant on the 99th percentile level.

In Model 4, street level fixed effects are added as well. The coefficients for Target*Post and Trend are weaker compared to Model 3, but still significant on the 99th percentile level. The coefficient for Trend shows that as the opening of the shopping center approaches, the average street level prices are increasing by 0.74% yearly, in both the target and control areas. The coefficient for Target*Post shows that the average street level price on streets located within the target area and observed after the opening of a shopping center is 3.24% higher compared to the control area.

Regression results for Model specifications: 1, 2, 3, 4

VARIABLES	(1)	(2)	(3)	(4)
Constant	5.7412	5.6569	5.7950	5.4973
Post	0.5089***			
	(0.0113)			
Target	-0.0182	-0.0605*	-0.0379	
	(0.0282)	(0.0329)	(0.0284)	
(Target * Post)	0.0123	0.0940***	0.0522***	0.0319***
	(0.0218)	(0.0250)	(0.0186)	(0.0100)
Trend			0.0221***	0.0074***
			(0.0046)	(0.0021)
Time fixed effects (sale years)	NO	YES	YES	YES
Location fixed effects (zip codes)	YES	YES	YES	NO
Street level fixed effects	NO	NO	NO	YES
Observations	4,194	4,194	4,194	4,194
R-squared	0.3467	0.8907	0.8966	
Within R-squared				0.9584
Overall R-squared				0.7525
F test	F(13, 232) = 271.96 p < 0.001	F(29, 232) = 1609.94 p < 0.001	F(30, 232) = 1311.23 p < 0.001	F(19, 232) = 1966.25 p < 0.001

Note: The dependent variable is ln Average Street Price.
Note: Standard errors are clustered on street level, and in parentheses with *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 4: regression results for model specifications: 1, 2, 3, 4

Using the Bacon decomposition and the ATET (Average Treatment Effect on the Treated), the high weight: 90.44%, of the "Treated vs Never Treated" component indicates that most of the variation in the ATET is coming from comparisons between units that received treatment and those that did not in the coefficient of Target*Post, the main variable of interest (Goodman-Bacon, 2021). This suggests that the differences between treated and never treated units are the most influential in determining the overall treatment effect, ensuring the reliability of the coefficient even with heterogenous treatment.

Overall, the main variable of interest Target*Post, which acts as the main difference in difference estimator is significant in the more specified models, indicating that the opening of a shopping center does influence average street level prices positively. Furthermore, the estimated coefficients for Trend, show that there exists an anticipation effect regarding shopping center openings.

4.2 Event study

To further investigate the effects of shopping center openings an event study is carried out within the target area. The results of the event study model specifications can be found in Table 5. The first model has an adjusted R-squared value of 0.9735 and the F test also indicates that the model results are highly significant. It shows that there is a significant positive effect already after one year of opening, as the average street level prices increase by 4.33% within the target area compared to one year before the opening. This effect is significant on the 95th percentile level. In year two, the effect becomes less significant, only at the 90th percentile level, but it increases to 4.6% compared to one year before the opening. However, the strongest effect is observed in year four after opening, as average street level prices increase by 10.15% compared to one year before the opening, with the effect being significant on the 95th percentile level. The further coefficients of the first model can be seen in Figure 1. In the second model, the adjusted R-squared is 0.9735, the F test also indicates that the model results are highly significant. The coefficient for the lead after 4 years is significant on the 99th percentile level and positive. It indicates that compared to one year before the opening, the average street level prices in the target area are 5.32% higher. A further significant coefficient is the lead after 5 years, which is positive and significant on the 90th percentile level. The further coefficients of the second model can be seen in Figure 2.

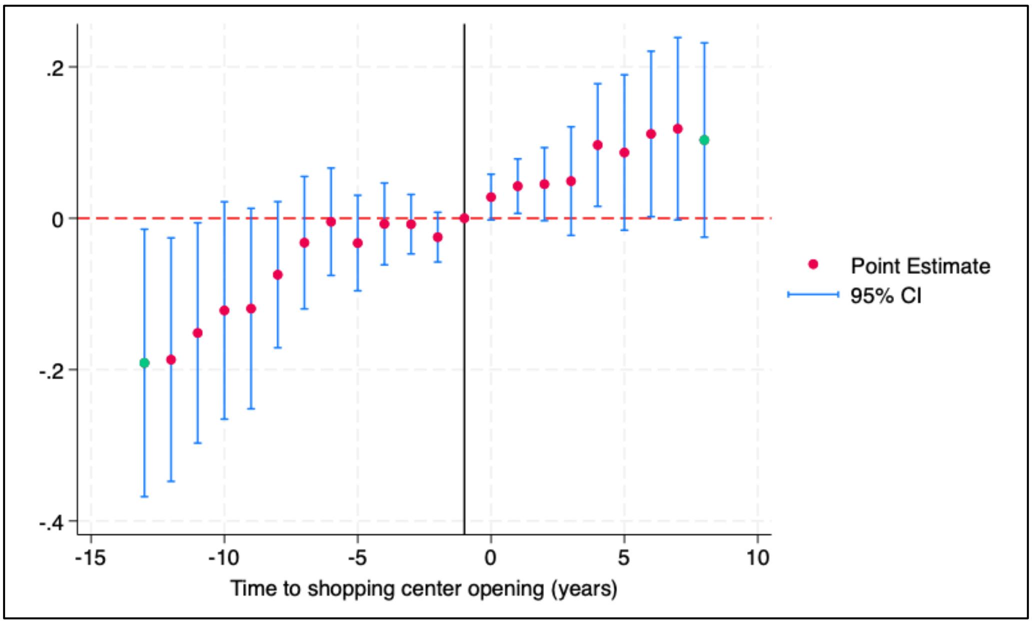


Figure 1: event study model 1

Regression results for the event study Model specifications: 1, 2

VARIABLES	(1)	(2)
Constant	5.4779	5.4373
Lag 2	-0.0250	-0.0192
	(0.0164)	(0.0198)
Lag 3	-0.0079	0.0091
	(0.0196)	(0.0183)
Lag 4	-0.0075	0.0143
	(0.0270)	(0.0226)
Lag 5	-0.0328	-0.0006
	(0.0316)	(0.0246)
Lag 6	-0.0046	0.0334
	(0.0355)	(0.0262)
Lead 1	0.0424**	0.0246
	(0.0180)	(0.0164)
Lead 2	0.0450*	0.0174
	(0.0242)	(0.0195)
Lead 3	0.0491	0.0138
	(0.0359)	(0.0173)
Lead 4	0.0967**	0.0519***
	(0.0405)	(0.0175)
Lead 5	0.0868*	0.0351*
	(0.0514)	(0.0199)
Time fixed effects (sale years)	YES	YES
Location fixed effects (zip codes)	NO	NO
Street level fixed effects	YES	YES
Observations	1,134	1,134
R-squared	0.9759	0.976
Adjusted R-squared	0.9735	0.9735
F test	$F(38, 62) = 772.64$ $p < 0.001$	$F(47, 1024) = 904.00$ $p < 0.001$

Note: The dependent variable is ln Average Street Price.
Note: Standard errors are clustered on street level in Model 1, robust in Model 2, and in parentheses with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Note: The other coefficients can be obtained from the author.

Table 5: regression results for the event study model specifications: 1, 2

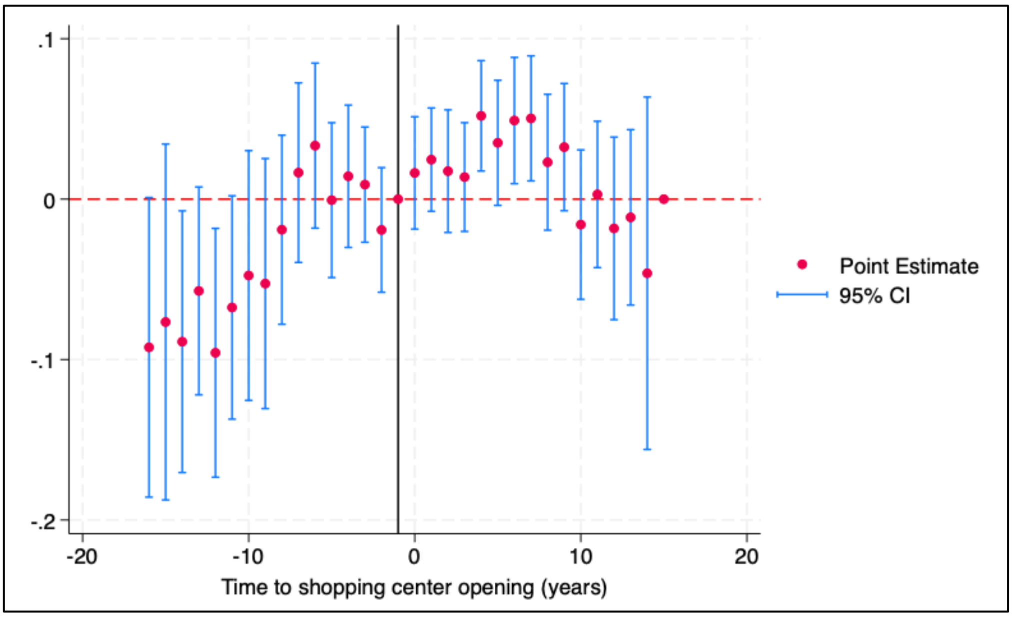


Figure 2: event study model 2

4.3 Heterogeneity

To estimate the stability of parameters a Chow-test was used, and location fixed effects were excluded so that the degrees of freedom would stay constant across the groups. The first parameter stability test was carried out based on the size of the shopping centers. Second, a parameter stability test was performed based on the shopping centers' locations.

4.3.1 Heterogeneity based on the size of shopping centers

The first parameter stability test was carried out based on the size of the shopping centers and the results can be found in Table 6. The two sub-groups were established based on the GLA of the shopping centers, with the first sub-group being the large shopping centers with over 20,000 square-meters of GLA and the other being the smaller shopping centers with 6,000 square-meters of GLA. The critical F value at 0.05 significance level is 1.5705. As the F statistics value of 98.7556 is higher than the critical F value, the null hypothesis is rejected and therefore, the parameters are not stable over time in the analysis and there is heterogeneity. This points to the fact that possibly larger and smaller shopping centers have varying levels of external effects on nearby properties. The coefficient of Target becomes significant in the second sub-group with small shopping centers, similar to the pooled model, but weaker. It indicates that the average street level price in streets located in the target area are 6.00% lower than for properties located in the control area, with the effect being significant on the 99th percentile level. The coefficient of Target*Post is strongly positive and significant on the 95th percentile level in the sub-group with large shopping centers, whereas it is insignificant in the sub-group with small shopping centers. Regarding large shopping centers, the average street level price on streets located within the target area and observed after the opening of a shopping center is 5.48% higher compared to the control area.

Parameter stability (Chow) test

VARIABLES	(1) Pooled Model	(2) Model with Large Shopping Centers	(3) Model with Small Shopping Centers
Constant	5.4653	5.3239	5.6065
Target	-0.0580***	0.0042	-0.0619***
	(0.0147)	(0.0171)	(0.0172)
(Target * Post)	0.0911***	0.0534**	0.0127
	(0.0179)	(0.0221)	(0.0201)
Time fixed effects (sale years)	YES	YES	YES
Location fixed effects (zip codes)	NO	NO	NO
R2	0.752	0.784	0.860
Adjusted R2	0.751	0.782	0.859
F test	F(19, 4174) = 665.18 Prob > F = 0.0000	F(19, 2194) = 419.19 Prob > F = 0.0000	F(19, 1960) = 633.59 Prob > F = 0.0000
RSS	295.9701	133.03846	67.5550175
sum of URSS		200.5934775	
k	20	20	20
m	2	2	2
T	4,194	2,214	1,980
F statistic		98.7556	
F value		(df1: 20 ; df2: 4154)	

Note: The dependent variable is ln Average Street Price.
Note: Standard errors in parentheses with *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 6: parameter stability test based on shopping center size

4.3.2 Heterogeneity based on the location of shopping centers

The second parameter stability test was carried out based on the location of the shopping centers and the results can be found in Table 7. The two sub-groups were established based on the location of the shopping centers, with the first sub-group being the shopping centers located in Buda, and the other being the shopping centers located in Pest. The critical F value at 0.05 significance level is 1.5705. As the F statistics value of 31.3396 is higher than the critical F value, the null hypothesis is rejected and therefore, the parameters are not stable over time in the analysis and there is heterogeneity. This highlights the fact that there are differing degrees of the levels of external effects on the two sides of the Danube. The coefficient of the Target variable is negative in both sub-groups, as well as significant on the 99th percentile level. However, in the sub-group with shopping centers located in Buda, it is much larger, meaning that the average street level price in a street located in the target area is 14.59% lower compared to the control area in Buda, while it is only 5.50% lower if the street located in Pest. The coefficient for Pest is more closely mirroring the coefficient for the pooled model, therefore there are more negative external effects on streets, associated with being within the target area in Buda. The coefficient for Target*Post is positive in both sub-groups, both more significant on the Buda sub-group, as it is significant on the 99th percentile level, while only being significant on the 95th percentile level in the sub-group with Pest shopping centers. In the Buda sub-group, it indicates that the average street level price on streets located within the target area and observed after the opening of a shopping center is 17.78% higher compared to the control area in Buda, but only 6.63% higher in Pest. This highlights that in the studied period there was a much more dynamic increase in street level housing prices in Buda compared to Pest, as well as the fact that the opening of a shopping center generates larger and more significant positive external effects in Buda, compared to Pest.

Parameter stability (Chow) test

	(1)	(2)	(3)
VARIABLES	Pooled Model	Model with Shopping Centers in Buda	Model with Shopping Centers in Pest
Constant	5.4653	5.6249	5.4091
Target	-0.0580***	-0.1578***	-0.0566***
	(0.0147)	(0.0159)	(0.0208)
(Target * Post)	0.0911***	0.1637***	0.0642**
	(0.0179)	(0.0195)	(0.0251)
Time fixed effects (sale years)	YES	YES	YES
Location fixed effects (zip codes)	NO	NO	NO
R2	0.752	0.844	0.753
Adjusted R2	0.751	0.842	0.752
F test	F(19, 4174) = 665.18 Prob > F = 0.0000	F(19, 1294) = 369.68 Prob > F = 0.0000	F(19, 2860) = 459.76 Prob > F = 0.0000
RSS	295.9701	48.3558575	208.810712
sum of URSS		257.1665695	
k	20	20	20
m	2	2	2
T	4,194	1,314	2,880
F statistic		31.3396	
F value		(df1: 20 ; df2: 4154)	

Note: The dependent variable is ln Average Street Price.

Note: Standard errors in parentheses with *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 7: parameter stability test based on shopping center location

4.4 Robustness check

As a robustness check, two first difference models are estimated, and the results can be found in Table 8. In Model 1, the R-squared value is low, but the F test indicates that the model results are significant. The coefficient for Target*Post is positive, and significant on the 99th percentile level, indicating that the average street level price on street located within the target area and observed after the opening of a shopping center is 3.08% higher compared to the control area. This is in line with the findings of Model 4. In the second first difference model, the Post variable is investigated within the target area. The R-squared value is similarly low, but the F test indicates that the model results are significant. Its coefficient is positive and significant on the 99th percentile level. It indicates that average street level prices are 6.97% higher after the opening of a shopping center in the target area. This value is high compared to the coefficients of the previous first difference model and Model 4. However, this could be attributed to the fact that we could not control for time fixed effects as it would interfere with the interpretation of the Post coefficient. Still, both coefficients of the robustness have the expected sign and significance.

Regression results for First Difference Model specifications: 1, 2

VARIABLES	(1)	(2)
Constant	0.0737	5.6569
Post		0.0674***
		(0.0069)
(Target * Post)	0.0303***	
	(0.0032)	
Time fixed effects (sale years)	NO	NO
Location fixed effects (zip codes)	YES	YES
Street level fixed effects	YES	YES
Observations	3,961	1,071
R-squared	0.0057	0.0496
F test	$F(11, 232) = 13.52$ $p < 0.001$	$F(7, 62) = 16.72$ $p < 0.001$

Note: The dependent variable is ln Average Street Price.
Note: Standard errors are clustered on street level, and in parentheses with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8: regression results for first difference model specifications: 1, 2

5. Discussion

This section will elaborate on the most important results and their implications, highlight the limitations of this study, and provide possible future directions for research.

The coefficient for Target was only significant in Model 2, however not significant in any of the other models. It means that in Model 2, streets that are in the target area have lower average street level prices compared to those in the control area by 5.87%. This highlights that the average street level price is lower before the opening of a shopping center, which could be due to the fact that many shopping centers were built on former brownfield sites, so their vicinity may have been a deteriorating area before the development (Sikos & Hoffmann, 2004). Zhang, et al. (2019) has found similarly lower housing prices in the target area before shopping center redevelopment, which could be due to the negative external effects of an outdated shopping center as it is an eye-sore to people living in the area. Therefore, shopping centers may have been built in undesirable plots of land, such as former brownfields of formerly industrial or rail network areas (Kukely, et al., 2006; Sikos & Hoffmann, 2004). However, based on the other models, there could be no effect established based on whether the street was located in the Target area or not. The coefficient for Target*Post, the main variable of interest, showed that the average street level prices on street located within the target area and observed after the opening of a shopping center are 3.24% higher compared to the control area. This effect is in line with the current literature: Rosiers, et al. (1996) found 5% increase in Canada, Kurvinen & Wiley (2019) found a 1.5% in Helsinki, Wilhelmsson & Long (2020) found an increase 1.4% in Stockholm, Yu, et al. (2012) found an increase of 2.5% to 3.0% in the USA, Pope & Pope (2015) found a 2–3% increase in the USA as well and Zhang, et al. (2019) found a 10% increase in China. Furthermore, this result answers the central research questions and confirms the first hypothesis. Therefore, the results of the paper at the 3.24% increase, align with international literature, which shows a range of 1.4% to 10% increase in property prices near shopping centers. The results are between the findings in Western Europe, in Helsinki and Stockholm, and the USA. The higher external effects than in Helsinki and Stockholm could be due to the effect of new shopping centers being place-based investments, in former brownfields improving the overall area. Regarding the differences with the results found in the USA, the different urban structure in Budapest, especially the extensive public transportation system, could mean that more people can access the shopping centers, and many may just walk by visit the shopping center unplanned, as highlighted in the literature regarding accessibility and the fact that shopping centers are increasingly places of leisure and social gathering (Czinkan & Horváth, 2019). Furthermore, Hungary being a developing country, it has different socio-economic characteristics which can also lead to these differences compared to Western Europe, the USA, or China (Beiró, et al., 2018).

The coefficient for Trend shows that as the opening of the shopping center is approaching, the average street level prices are increasing by 0.74% yearly in both the target and control areas. This highlights that there is an anticipation effect, so the average street level prices are growing even before the opening, after the announcement, in line with what Colwell, et al. (1985) has found as well. Similarly, Zhang, et al. (2019) has found that while there is no increase in housing prices before the opening, there is increased transaction activity in the area surrounding the shopping center.

In the event study, both model specifications indicated that after the opening of a shopping center, average street level property prices in the target area are increasing, however only four years after the opening of a shopping center was confirmed as a significant increase. This is more than the findings of Zhang, et al. (2019), that prices are the highest until 2 years and then it decays. This finding answers the second research question but slightly contrasts to the related hypothesis of an increase right after opening. It is possible that the positive effect on average street level property prices is only observed after four years, because not all retail units may be let out already at the time of the opening and it takes time until all units are occupied, creating a wider selection of stores. Furthermore, it may take a few years to develop the appropriate tenant mix, including key anchor tenants, both of which have been shown to be important in the external effects of the shopping centers above. Lastly, some shopping centers built, such as Arena Mall, have been struggling severely with units not let out in the first years of their operation, as they were built in former brownfields and had limited access by public transport (Demeter, 2014).

In the heterogeneity test regarding the size of the shopping centers, the coefficient of Target*Post was insignificant in the case of small shopping centers, while showing that the average street level price on streets located within the target area and observed after the opening of a shopping center are 5.48% higher compared to the control area regarding large shopping centers. This highlights that larger shopping centers do exhibit larger positive external effects, which could be possibly attributed to the more leisure facilities provided by them, such as cinemas, the better availability of parking, a larger selection of tenants, a more diverse tenant mix, and more anchor tenants. This finding answers the third research question and aligns with the third hypothesis.

In the heterogeneity test regarding the location of the shopping centers, being in either Buda or Pest, the coefficient of Target*Post was significant in both sub-groups and showed that the average street level price on streets located within the target area and observed after the opening of a shopping center are 17.78% higher compared to the control area in Buda, but only 6.63% higher in Pest. This highlights that the opening of a shopping center has a larger effect in Buda than in Pest. This finding answers the third research question and aligns with the third hypothesis. The difference could possibly be due to the topography and terrain of Buda, as Hilber (2017) indicates that in areas where housing supply is constrained due to geographic factors, amenities are more capitalized into housing prices. Furthermore, the fact that the Target variable is more strongly negative in the Buda sub-group, could be because there is more car usage in Buda due to the terrain, as well as public transport is served more by buses rather than the metro as in Pest, meaning more negative effects for being close to a shopping center with higher levels of traffic (Horváth & Soóki-Tóth, 2014). This is also similar to the findings in other literature of a closer inner ring where negative external effects outweigh the positive effects (Colwell, et al., 1985; Sirpal, 1994).

This study yields meaningful insights into the effects of shopping center openings in Budapest, Hungary, a major economic hub in the CEE region, providing generalisable insights into real estate investment in Budapest and the region. The findings of the study can be employed by residential real estate investors, logistics planners, retailing planners and housing management practitioners who want to understand the ambiguous effects of shopping center openings on nearby residential property prices. These insights can also be utilised by retail investors, who may have other projects surrounding their shopping center development, or who want to understand the effect of their development on surrounding housing prices. These insights can be utilised by local investors, as well as international investors searching for higher-yielding assets in their portfolios, as the weight of alternative investments is growing globally.

Furthermore, this study generates various insights for policymakers and land use planners. The results of the effects of shopping centers on housing prices can be taken as a basis for land use planning by the government, the municipality of Budapest or the governing bodies of the districts. It can also highlight how the introduction of a shopping center and such retail facilities can influence the housing prices in newly built areas of the city, such as BudaPart and Marina City (Cordia, 2024; Property Market, 2024). The event -study yields insights into the temporal external effects of shopping center openings, which can be utilised by city planners to prepare for potential affordability issues in the given timeframe, due to the increase in housing prices, affecting people with lower socio-economic backgrounds negatively. Furthermore, due to a law introduced in Hungary in 2012, called colloquially “plaza-stop”, which was aimed at banning the further building of large shopping centers, so that commercial units larger than 400 sqm could not be built, therefore these findings will remain resilient over time until there is a change in legislation and the real estate markets react, which is a lengthy process (DiPasquale & Wheaton, 1992; Hungarian Government Decree, 2023).

5.1 Limitations

Limitations of this study include the relatively low number of observations, stemming from the data structure of street-level observations. A further limitation of the study is the relatively short time span of the data, being only from 2005 until 2022. This has limited the number of shopping centers which can be studied, as only eight shopping centers opened in this period in Budapest.

5.2 Future research

Future research could verify the findings of this study using individual housing transactions. Furthermore, future research could also investigate the effect of other types of shopping establishments, as it has been suggested by Yu, et al. (2012), that supermarkets boast a positive effect as they are part of basic infrastructure and have been found to generate house price increase by Shen, et al. (2020). Further research could also identify and compare the size of the differing impact on house prices regarding the catchment area of the shopping center, and how the impact patterns differ at different scales and operational levels of the shopping centers. Lastly, further research could investigate, how areas that are only accessible by car to the shopping center, such as the suburbs around Budapest which have been growing rapidly, benefit from the opening of shopping center (Timar & Váradi, 2001).

6. Conclusion

This study has employed a difference-in-difference methodology to measure the external effects of shopping center openings in Budapest, Hungary. It utilized aggregate street level housing transaction data of 233 streets, and used 8 shopping centers, investigating the period from 2005 until 2022. It has found that the average street level price on street located within the target area and observed after the opening of a shopping center are 3.24% higher compared to the control area. It has also found evidence of an anticipation effect, namely that as the opening of the shopping center approaches, the average street level prices are increasing by 0.74% yearly in both the target and control areas. Using an event study, it found that average street-level property prices in the target area are higher four years after the opening of a shopping center. Furthermore, larger shopping centers exhibited a larger external effect, and the external effects were larger in Buda compared to Pest. This highlights and confirms that there are major differences in terms of housing market processes and characteristics between Buda and Pest, in line with previous academic and industry findings (Cushman&Wakefield, 2024; Eltinga, 2023; Horváth & Soóki-Tóth, 2014).

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8. Appendices

8.1 Appendix A: List of shopping centers

Shopping centers:

- Arena Mall: (https://www.arenamall.hu/en/)
- Corvin Plaza: (https://corvinplaza.hu/)
- KOKI Terminal: (https://kokibevasarlokozpont.hu/)
- Etele Plaza: (https://eteleplaza.hu/)
- Arkad Budapest II: (https://www.arkadbudapest.hu/en/)
- Allee Shopping Mall: (https://allee.hu/en)
- Europeum: (https://europeum.hu/en/)
- Hegyvidek Bevasarlokozpont: (https://hegyvidekkozpont.hu/en)

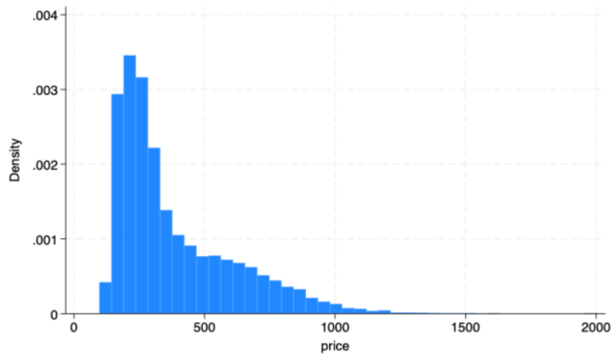
8.2 Appendix B: Results from the target area determination

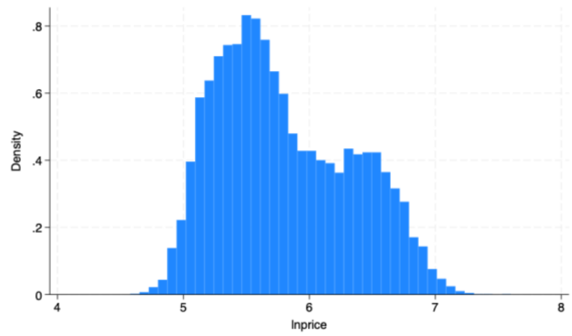
Regression results for the target area determination

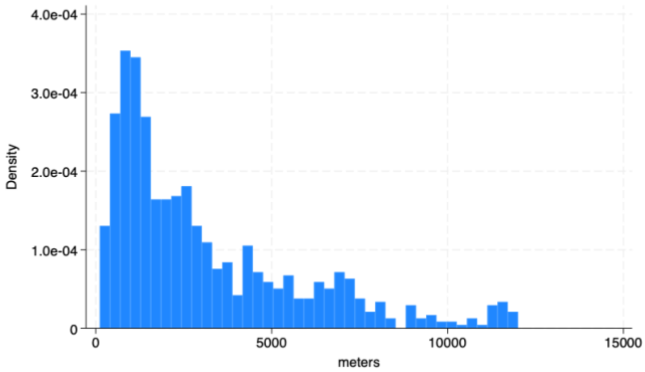
VARIABLES	(1)
Constant	5.6978
Post	0.0369***
	(0.0055)
0-250 m	0.1275***
	(0.0165)
250-500 m	0.0415***
	(0.0123)
500-750 m	0.0309***
	(0.0118)
750-1000 m	0.0229**
	(0.0112)
1000-1250 m	-0.0153
	(0.0113)
1250-1500 m	0.0034
	(0.0114)
1500-1750 m	-0.0229**
	(0.0125)
1750-2000 m	0.0195
	(0.0126)
2000-2250 m	0.0026
	(0.0117)
Time fixed effects (years)	YES
Location fixed effects (zip codes)	YES
Observations	14,760
R2	0.8901
Adjusted R2	0.8897
F test	F(55, 14704) = 2165.13 p < 0.001

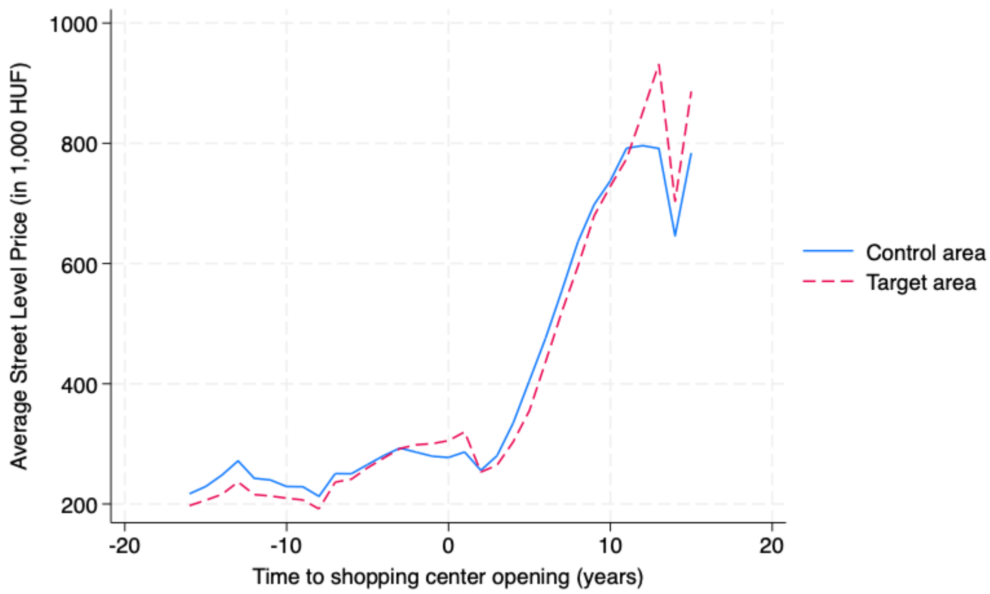
Note: The dependent variable is ln Average Street Price.
Note: Standard errors in parentheses with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Note: The other coefficients can be obtained from the author.

8.3 Appendix C: Results of assumption testing







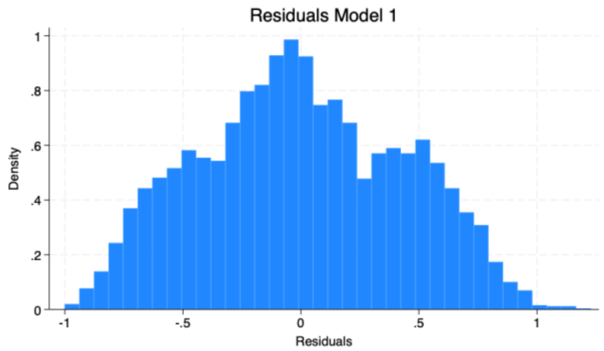


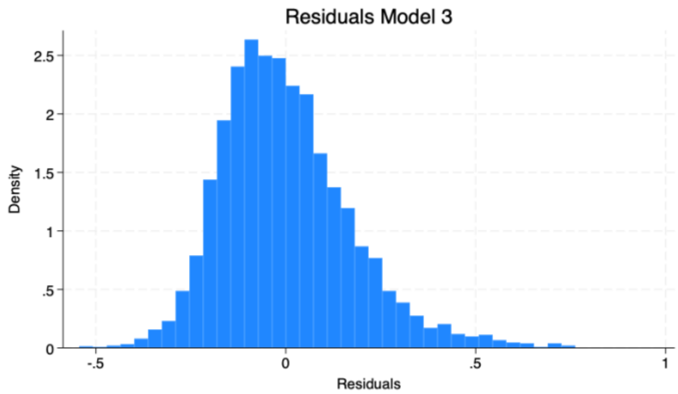
Correlation matrix								
Variable	Average Street Price	Log of Average Street Price	Distance	Time to Shoping Mall Opening	Post	Trend	Target	(Target * Post)
Average Street Price	1.0000							
Log of Average Street Price	0.9655	1.0000						
Distance	0.0013	-0.0034	1.0000					
Time to Shoping Mall Opening	0.6849	0.6841	0.0307	1.0000				
Post	0.4309	0.4385	0.0214	0.8063	1.0000			
Trend	0.3553	0.3729	0.0637	0.8115	0.7441	1.0000		
Target	-0.0021	0.0001	-0.8085	-0.0105	-0.0073	-0.0337	1.0000	
(Target * Post)	0.1504	0.1588	-0.6120	0.2844	0.3398	0.2529	0.7497	1.0000

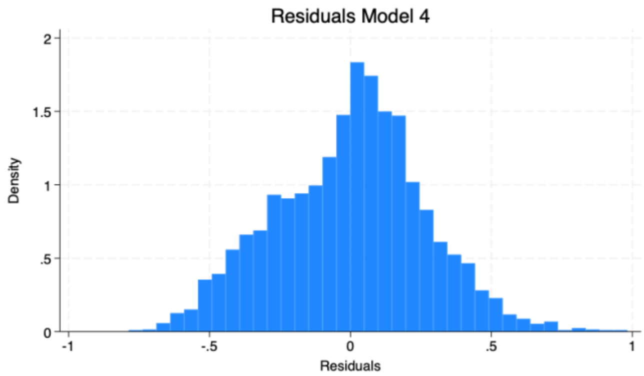
VIF table for Model 1	
Variable	VIF
Post	1.400
Target	2.940
(Target * Post)	3.150
Location fixed effects	-
Mean VIF	6.480

VIF table for Model 2	
Variable	VIF
Target	2.730
(Target * Post)	2.730
Time fixed effects	-
Location fixed effects	-
Mean VIF	3.970

VIF table for Model 3	
Variable	VIF
Target	2.790
Trend	2.360
(Target * Post)	2.880
Time fixed effects	-
Location fixed effects	-
Mean VIF	4.140







8.4 Appendix D: STATA code

```
ssc install geonear
ssc install geodist
ssc install eventdd
ssc install matsort
ssc install reghdfe
ssc install ftools

import excel using "/Users/petercsitkovics/Documents/Documents/Real Estate/RE Thesis/Data/csitko gold.xlsx", firstrow clear

foreach var of varlist _all {
   label variable `var' ""
}

save streets.dta, replace

import excel using "/Users/petercsitkovics/Documents/Documents/Real Estate/RE Thesis/Data/shopping malls.xlsx", firstrow clear

foreach var of varlist _all {
   label variable `var' ""
}

save malls.dta, replace

use "streets.dta", clear

geonear ID latitude longitude using "malls.dta", n(mall_name latitude1 longitude1)

/// ID variable was created by adding streets and distircits together in excel

gen meters = km_to_nid * 1000
```

```
gen id = _n

order id

reshape long year_ , i(id) j(year)

rename year_ price

encode ID, gen(ID1)

xtset ID1 year

rename nid mall_name

merge m:1 mall_name using malls.dta

drop _merge

gen post_opening = year >= year_opened

gen before_opening = year <= year_opened

gen eventX = .

replace eventX = 2009 if mall_name == "Allee Shopping Mall"

replace eventX = 2007 if mall_name == "Arena Mall"

replace eventX = 2010 if mall_name == "Corvin Plaza"

replace eventX = 2011 if mall_name == "KOKI Terminal"

replace eventX = 2011 if mall_name == "Europeum"
```

```
replace eventX = 2012 if mall_name == "Hegyvidek Bevasarlokozpont"

replace eventX = 2013 if mall_name == "Arkad Budapest II"

replace eventX = 2021 if mall_name == "Etele Plaza"

gen time_to_event = year - eventX

hist price

gen lnprice = ln(price)

hist lnprice

hist meters

//////data summary

sum price lnprice meters time_to_event

///////////////////////////creating the rings

//////0-250

gen between_0_250 = (meters > 0 & meters <= 250)

gen int_0_250 = post_opening * between_0_250

/////250-500

gen between_250_500 = (meters > 250 & meters <= 500)

gen int_250_500 = post_opening * between_250_500
```

```
/////500-750

gen between_500_750 = (meters > 500 & meters <= 750)

gen int_500_750 = post_opening * between_500_750

//////750-1000

gen between_750_1000 = (meters > 750 & meters <= 1000)

gen int_750_1000 = post_opening * between_750_1000

//////1000-1250

gen between_1000_1250 = (meters > 1000 & meters <= 1250)

gen int_1000_1250 = post_opening * between_1000_1250

//////1250-1500

gen between_1250_1500 = (meters > 1250 & meters <= 1500)

gen int_1250_1500 = post_opening * between_1250_1500

//////1500-1750

gen between_1500_1750 = (meters > 1500 & meters <= 1750)

gen int_1500_1750 = post_opening * between_1500_1750

//////1750-2000

gen between_1750_2000 = (meters > 1750 & meters <= 2000)
```

```
gen int_1750_2000 = post_opening * between_1750_2000

//////2000-2250

gen between_2000_2250 = (meters > 2000 & meters <= 2250)

gen int_2000_2250 = post_opening * between_2000_2250

//////2250-2500

gen between_2250_2500 = (meters > 2250 & meters <= 2500)

gen int_2250_2500 = post_opening * between_2250_2500

//////2500-3000

gen between_2500_3000 = (meters > 2500 & meters <= 3000)

gen int_2500_3000 = post_opening * between_2500_3000

//////3000-3500

gen between_3000_3500 = (meters > 3000 & meters <= 3500)

gen int_3000_3500 = post_opening * between_3000_3500

//////3500-4000

gen between_3500_4000 = (meters > 3500 & meters <= 4000)

gen int_3500_4000 = post_opening * between_3500_4000

//////4000-4500
```

gen between_4000_4500 = (meters > 4000 & meters <= 4500)

gen int_4000_4500 = post_opening * between_4000_4500

//////4500-5000

gen between_4500_5000 = (meters > 4500 & meters <= 5000)

gen int_4500_5000 = post_opening * between_4500_5000

////////////////determining the target area

reg lnprice post_opening between_0_250 between_250_500 between_500_750 between_750_1000 between_1000_1250 between_1250_1500 between_1500_1750 between_1750_2000 between_2000_2250 between_2250_2500 between_2500_3000 between_3000_3500 between_3500_4000 between_4000_4500 between_4500_5000 i.year i.district

/////////////Displaying results for target area

collect clear
collect label list result0
collect create model0
collect _r_b _r_se _r_p: reg lnprice post_opening between_0_250 between_250_500 between_500_750 between_750_1000 between_1000_1250 between_1250_1500 between_1500_1750 between_1750_2000 between_2000_2250 between_2250_2500 between_2500_3000 between_3000_3500 between_3500_4000 between_4000_4500 between_4500_5000 i.year i.district
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

///////////////////////

drop if meters > 1500

///////////////////////calcualting the distance each street to each shopping mall

geodist 47.4979348314151 19.0943190400466 latitude longitude, generate(dist_to_Arena)

geodist 47.4742714049378 19.0487750639241 latitude longitude, generate(dist_to_Allee)

geodist 47.4857510268769 19.0744073841559 latitude longitude, generate(dist_to_Corvin)

geodist 47.4622624408166 19.1490858594001 latitude longitude, generate(dist_to_KOKI)

geodist 47.4961730228001 19.0697911271579 latitude longitude, generate(dist_to_Europeum)

geodist 47.4911746189352 19.0112995316083 latitude longitude, generate(dist_to_Hegyvidek)

geodist 47.5030568512657 19.1414822403612 latitude longitude, generate(dist_to_Arkad)

geodist 47.4638529495359 19.0236885553885 latitude longitude, generate(dist_to_Etele)

////////////////dropping streets which overlap in control and target area

gen dummy_Arena = dist_to_Arena <= 1.5

gen dummy_Alle = dist_to_Allee <= 1.5

gen dummy_Corvin = dist_to_Corvin <= 1.5

gen dummy_KOKI = dist_to_KOKI <= 1.5

```
gen dummy_Europeum = dist_to_Europeum <= 1.5

gen dummy_Hegyvidek = dist_to_Hegyvidek <= 1.5

gen dummy_Arkad = dist_to_Arkad <= 1.5

gen dummy_Etele = dist_to_Etele <= 1.5

gen overlap = dummy_Arena + dummy_Alle + dummy_Corvin + dummy_KOKI + dummy_Europeum + dummy_Hegyvidek + dummy_Arkad + dummy_Etele

drop if overlap > 1

/////////////Regressions

gen within_750 = meters <= 750

gen int750 = post_opening * within_750

//////data summary for target and control areas

sum price lnprice meters time_to_event if within_750 == 1

sum price lnprice meters time_to_event if within_750 == 0

//////export data to Excel for map

preserve

keep ID1 latitude longitude

duplicates drop ID1, force
```

```
export excel using "dataset for GIS", replace

restore

/////////////paralell trend assumption

bysort time_to_event within_750: egen mean_tte_price = mean(price)

twoway line mean_tte_price time_to_event if within_750 == 0, sort || line mean_tte_price time_to_event if within_750 == 1, sort lpattern(dash) legend(label(1 "Control area") label(2 "Target area")) xtitle("Time to shopping center opening (years)") ytitle("Average Street Level Price (in 1,000 HUF)")

/////////////Model 1

reg lnprice post_opening within_750 int750 i.district, vce(cluster ID1)

predict e_Model1, res

histogram e_Model1, title("Residuals Model 1")

estat vif

/////////////Displaying results for Model 1

collect clear
collect label list result1
collect create model1
collect _r_b _r_se _r_p: reg lnprice post_opening within_750 int750 i.district, vce(cluster ID1)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview
```

```
/////////////Model 2

reg lnprice within_750 int750 i.year i.district, vce(cluster ID1)

predict e_Model2, res

histogram e_Model2, title("Residuals Model 2")

estat vif

/////////////Displaying results for Model 2

collect clear
collect label list result2
collect create model2
collect _r_b _r_se _r_p: reg lnprice within_750 int750 i.year i.district, vce(cluster ID1)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////Model 3

gen trend = time_to_event * before_opening

reg lnprice within_750 trend int750 i.year i.district, vce(cluster ID1)

predict e_Model3, res

histogram e_Model3, title("Residuals Model 3")

estat vif
```

```
/////////////Displaying results for Model 3

collect clear
collect label list result3
collect create model3
collect _r_b _r_se _r_p: reg lnprice within_750 trend int750 i.year i.district, vce(cluster ID1)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////Model 4

xtset ID1 year

xtreg lnprice int750 trend i.year, fe vce(cluster ID1)

predict e_Model4, res

histogram e_Model4, title("Residuals Model 4")

/////////////Bacon-Goodman decomposition

xtdidregress (lnprice) (int750), group(ID1) time(year)

estat bdecomp

/////////////Displaying results for Model 4

collect clear
collect label list result4
collect create model4
```

```
collect _r_b _r_se _r_p: xtreg lnprice int750 trend i.year, fe vce(cluster ID1)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////correlation matrix

corr price lnprice meters time_to_event post_opening trend within_750 int750

/////////////Event study for the number of years opening has an impact, Model 1

preserve

drop if meters > 750

tab time_to_event

eventdd lnprice i.year, hdfe absorb(ID1) vce(cluster ID1) timevar(time_to_event) leads(13) lags(8) accum graph_op(xtitle("Time to shopping center opening (years)"))

/////////////Displaying results for the event study Model 1

collect clear
collect label list result4
collect create model4
collect _r_b _r_se _r_p: eventdd lnprice i.year, hdfe absorb(ID1) vce(cluster ID1) timevar(time_to_event) leads(13) lags(8) accum
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview
```

```
/////////////Event study Model 2

eventdd lnprice i.year, hdfe absorb(ID1) vce(robust) timevar(time_to_event) graph_op(xtitle("Time to shopping center opening (years)"))

/////////////Displaying results for the event study Model 2

collect clear
collect label list result5
collect create model5
collect _r_b _r_se _r_p: eventdd lnprice i.year, hdfe absorb(ID1) vce(robust) timevar(time_to_event)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

restore

/////////////Robustness test

/////////////Robustness test: first difference model

preserve

sort ID1 year

by ID1: gen lag_lnprice = lnprice[_n-1]

by ID1: gen lag_year = year[_n-1]

gen log_diff = lnprice - lag_lnprice if (year == lag_year + 1 | ID1 == ID1)
```

```
drop if missing(log_diff)

/////////////first difference model 1

reg log_diff int750 i.district, vce(cluster ID1)

/////////////Displaying results for first difference model 1

collect clear
collect label list result5
collect create model5
collect _r_b _r_se _r_p: reg log_diff int750 i.district, vce(cluster ID1)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////first difference model 2

drop if meters > 750

reg log_diff post_opening i.district, vce(cluster ID1)

/////////////Displaying results for first difference model 2

collect clear
collect label list result5
collect create model5
collect _r_b _r_se _r_p: reg log_diff post_opening i.district, vce(cluster ID1)
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
```

```
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

restore

/////////////Heterogeneity (Chow test) based on mall GLA

gen large_mall = mall_name == "Arena Mall" | mall_name == "Corvin Plaza" | mall_name == "KOKI Terminal" | mall_name == "Etele Plaza" | mall_name == "KOKI Terminal" | mall_name == "Arkad Budapest II"

/////////////pooled model

reg lnprice within_750 int750 i.year

/////////////Displaying results for pooled model

collect clear
collect label list result6
collect create model6
collect _r_b _r_se _r_p: reg lnprice within_750 int750 i.year
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////large malls

reg lnprice within_750 int750 i.year if large_mall == 1

/////////////Displaying results for large malls

collect clear
```

```
collect label list result7
collect create model7
collect _r_b _r_se _r_p: reg lnprice within_750 int750 i.year if large_mall == 1
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////small malls

reg lnprice within_750 int750 i.year if large_mall == 0

/////////////Displaying results for small malls

collect clear
collect label list result8
collect create model8
collect _r_b _r_se _r_p: reg lnprice within_750 int750 i.year if large_mall == 0
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////Heterogeneity (Chow test) based on location

gen buda = mall_name == "Etele Plaza" | mall_name == "Hegyvidek Bevasarlokozpont" |
mall_name == "Allee Shopping Mall"

/////////////pooled model

reg lnprice within_750 int750 i.year
```

```
/////////////malls located in buda

reg lnprice within_750 int750 i.year if buda == 1

/////////////Displaying results for malls located in buda

collect clear
collect label list result9
collect create model9
collect _r_b _r_se _r_p: reg lnprice within_750 int750 i.year if buda == 1
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview

/////////////malls located in pest

reg lnprice within_750 int750 i.year if buda == 0

/////////////Displaying results for malls located in pest

collect clear
collect label list result10
collect create model10
collect _r_b _r_se _r_p: reg lnprice within_750 int750 i.year if buda == 0
collect style cell, nformat(%5.4f)
collect layout (colname) (result)
collect stars _r_p 0.01 "***" 0.05 "** " 0.1 "* " 1 " ", attach(_r_b)
collect notes : "*** p<.01, ** p<.05, * p<.1"
collect preview
```

8.5 Appendix E: Data management plan

Template Research Data Management Plan

Instructions: this is the template for a data management plan. Please fill this in and discuss it with your supervisor during the design phase of the thesis. If your thesis is nearly complete, please add this as an appendix to the thesis. The purpose of making a dmp to think ahead. How will you manage the data gathered for your project? It is not about providing the 'right' answers, but making your research transparent. Some items just require ticking, some require further explanation.

1. General	
1.1 Name & title of thesis	Péter Csitkovics: External effects of shopping center opening in Budapest, Hungary
1.2 *(if applicable)* Organisation. Provide details on the organisation where the research takes place if this applies (in case of an internship).	

2 Data collection – the creation of data	
2.1. Which data formats or which sources are used in the project? For example: - theoretical research, using literature and publicly available resources - Survey Data - Field Data - Interviews	Provide a short description of the sources/data that you are going to use. The thesis utilises a publicly available database based on real estate transaction reported on street level across Hungary, provided by the Hungarian Statistical Office (KSH).
2.2 Methods of data collection What method(s) do you use for the collection of data. (Tick all boxes that apply)	☐Structured individual interviews ☐Semi-structured individual interviews ☐Structured group interviews ☐Semi-structured group interviews ☐Observations ☐Survey(s) ☐Experiment(s) in real life (interventions) ☑ Secondary analyses on existing data sets (if so: please also fill in 2.3) ☐Public sources (e.g. University Library) ☐Other (explain):
2.3. (If applicable): if you have selected 'Secondary analyses on existing datasets': who provides the data set?	☐ Data is supplied by the University of Groningen. ☑ Data have been supplied by an external party. (Please mention the party here).

3 Storage, Sharing and Archiving	
3.1 Where will the (raw) data be stored *during* research? If you want to store research data, it is good practice to ask yourself some questions: • How big is my dataset at the end of my research?	☐X-drive of UG network ☐Y-drive of UG network ☐(Shared) UG Google Drive ☐Unishare ☑Personal laptop or computer ☐External devices (USB, harddisk, NAS)

• Do I want to collaborate on the data? • How confidential is my data? • How do I make sure I do not lose my data? Need more information? Take a look at the site of the Digital Competence Centre (DCC)) Feel free to contact the DCC for questions: dcc@rug.nl	☐Other (explain):
3.2 Where are you planning to store / archive the data after you have finished your research? Please explain where and for how long. Also explain who has access to these data NB do not use a personal UG network or google drive for archiving data!	☑X-drive of UG network ☑Y-drive of UG network ☐(Shared) UG Google Drive ☐Unishare ☐In a repository (i.e. DataverseNL) ☐Other (explain): The retention period will be [...] years.
3.3 Sharing of data With whom will you be sharing data during your research?	☐University of Groningen ☐Universities or other parties in Europe ☐Universities or other parties outside Europe ☑I will not be sharing data

4. Personal data	
4.1 Collecting personal data Will you be collecting personal data? If you are conducting research with personal data you have to comply to the General Data Privacy Regulation (GDPR). Please fill in the questions found in the appendix 3 on personal data.	Yes/no
If the answer to 4.1 is 'no', please skip the section below and proceed to section 5	
4.2 What kinds of categories of people are involved? Have you determined whether these people are vulnerable in any way (see FAQ)? If so, your supervisor will need to agree.	My research project involves: ☐Adults (not vulnerable) ≥ 18 years ☐Minors < 16 years ☐Minors < 18 years ☐Patients ☐ (other) vulnerable persons, namely (please provide an explanation what makes these persons vulnerable) (Please give a short description of the categories of research participants that you are going to involve in your research.)
4.3 Will participants be enlisted in the project without their knowledge and/or consent? (E.g., via covert observation of people in public	Yes/no If yes, please explain if, when and how you will

places, or by using social media data.)	inform the participants about the study.
4.4 Categories of personal data that are processed. Mention all types of data that you systematically collect and store. If you use particular kinds of software, then check what the software is doing as well. Of course, always ask yourself if you need all categories of data for your project.	☐Name and address details ☐Telephone number ☐Email address ☐Nationality ☐IP-addresses and/or device type ☐Job information ☐Location data ☐Race or ethnicity ☐Political opinions ☐Physical or mental health ☐ Information about a person's sex life or sexual orientation ☐Religious or philosophical beliefs ☐Membership of a trade union ☐Biometric information ☐Genetic information ☐ Other (please explain below):
4.5 Technical/organisational measures Select which of the following security measures are used to protect personal data.	☐Pseudonymisation ☐Anonymisation ☐File encryption ☐Encryption of storage ☐Encryption of transport device ☐Restricted access rights ☐VPN ☐Regularly scheduled backups ☐Physical locks (rooms, drawers/file cabinets) ☐None of the above ☐Other (describe below):
4.6 Will any personal data be transferred to organisations within countries outside the European Economic Area (EU, Norway, Iceland and Liechtenstein)? If the research takes places in a country outside the EU/EEA, then please also indicate this.	Yes/no If yes, please fill in the country.
5 - Final comments	
Do you have any other information about the research data that was not addressed in this template that you think is useful to mention?	