ASSESSING THE EFFECT OF BIKE LANE CONSTRUCTION ON SURROUNDING PROPERTY VALUES IN PARIS, FRANCE

- A Quantitative Approach -

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ABSTRACT

City planners in the French capital city of Paris are implementing an extensive network of bike paths in the city, called the *'Plan Vélo'*. A thorough understanding of the effect of the construction of bike infrastructure on property prices in the city will help planners to better substantiate their bike-friendly interventions and remove opposition. This research uses a difference-in-difference approach to investigate the effects of the construction of bike infrastructure on nearby residential property prices at five locations in Paris, France. Using a dataset of 6,741 observations from 2014 till 2019, the result of this research is that no significant effect of bike lane construction on property prices has been found. This means that Parisian house buyers do not consider nearby bike paths to be important assets when buying a house; bike lane proximity does not result in any difference in the price paid for residential properties after the construction of the bike infrastructure. This insignificant effect was found for both REV and non-REV bike lanes in the city and persisted when moving away from the bike infrastructure. Further research should be carried out to see whether this conclusion sustains over a longer period of time after construction as well.

Key words: difference-in-difference approach, bike infrastructure, property values, real estate, Paris

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1] INTRODUCTION

In cities all over the world, there is growing attention towards investments in bike infrastructure. While cities have been planned around car infrastructure for the past decennia, focus in inner cities in the Western World is shifting towards creating pedestrian and bike friendly cities and a rejection of the old forms of urbanization that were centred around the automobile (Rice, et al., 2019). An example is the car-free area in the city centre of Copenhagen, where biking is prioritized over car use (Gössling, 2013). Promoting bike infrastructure in cities can have multiple aims, like promoting an environmentally-friendly mode of transport, improving the health of city dwellers or decreasing journey times by lowering congestions in the city (Bullock, et al., 2016).

Paris, France, is one of the cities competing to become one of the most bike-friendly cities in the world. Convinced by the benefits of promoting bike use in the city, the new mayor of Paris, Anne Hildago, has shifted great amounts of tax money into constructing bike infrastructure in the city of Paris. The Parisian *Plan Vélo* (bike plan) has the aim to transform Paris into a *Ville du Quart d'Heure* (city of fifteen minutes), in which Parisians can reach all their daily needs within fifteen minutes biking (Sisson, 2020). According to this ambitious plan, every street and bridge in the city should have a bike lane in 2024, removing 72% of the car parking spaces on the streets. The plan includes more restrictions on car use, the introduction of bike-sharing stations in the city and a comprehensive expansion of bike lanes in the French capital.

New biking infrastructure in the city consists of a 1.95 meters wide biking lane at both sides of the roads. For an example of the design of the bike lanes, see **figure 1**. The bike lanes provide a safe place to bike, because they are separated from the road by barriers. Although tourists may use the bike infrastructure as well, the main aim of the programme is to improve access to bike infrastructure for the residents of the city and to nudge them to use the bike for their daily commute. At the moment, around 56% of the planned bike infrastructure for the city have been satisfactory completed (Observatoire du Plan Vélo de Paris, 2020).

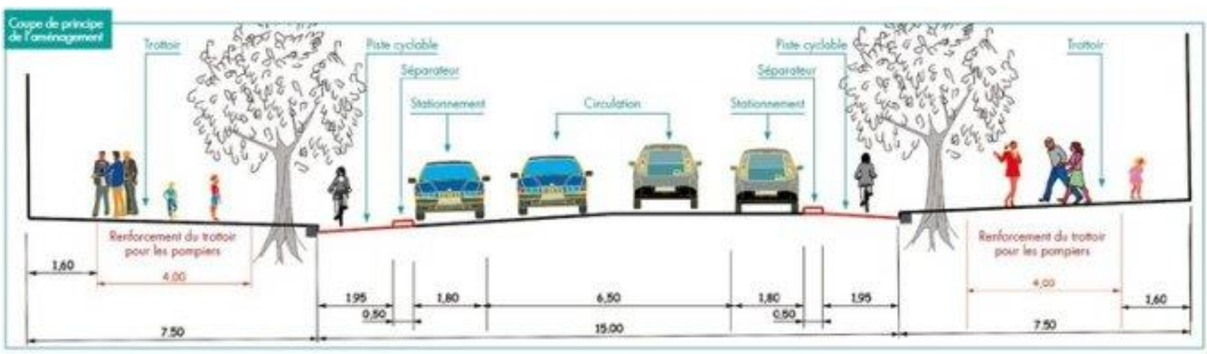

Figure 1: Example of bike lane design in Paris: the design for the bike lanes at both sides of Boulevard Voltaire. Source: Observatoire du Plan Vélo (2020).

Central in the design of the *Plan Vélo* are the Réseaux Express Vélo (REVs), which function as the main biking corridors in Paris. The design of the REVs is not very different from the design of 'regular' new bike infrastructure. However, as main biking routes in the city of Paris, the number of bike users on these REVs is bigger than on other bike trails. The next phase of the plans will focus on expanding the bike paths to the suburbs of *Île de France* (the Parisian Metropolitan Region) as well, to make sure that all parts of the city are evenly covered by the bike infrastructure.

The bike-friendly efforts in the city of Paris have not been in vain; Some recent numbers show the effects of the growing efforts to transform Paris into a bike-friendly city. From 2018 to 2019, the number of Parisians taking a bike for daily commute rose by 54% to 840,000 trips per day. Car traffic in the city saw a drop of 5% since 2010 (Sisson, 2020). On the Copenhagenize-index, an index ranking the most bike-friendly cities in the world, Paris has moved up from the 13th place in 2017 to the 8th place in 2019 (Copenhagenize, 2019).

The bike plans in Paris have, however, been met with fierce opposition as well, for example from the French car owners' association. Also, in public opinion, many Parisians still do not understand why so many expenses are made for a mode of transport that in total still sits under 7% of all traffic in Paris. According to Copenhagenize (2019), in Paris, *"additional funding should be put towards clear communications of the benefits of cycling for Parisians".* This means that city planners in Paris need clear information about the welfare benefits of cycling for the city.

Research that investigates the quantitative effect of constructing bike infrastructure on property prices could help investigating the matter. The outcome of this research will provide new evidence that can be used in the public debate in Paris about the bicycle infrastructure. For example, if this research provides evidence for a significant negative effect of the bike lanes on property prices, city dwellers could demand compensations or changes to the plans from their city government. The welfare losses or gains of the bicycle infrastructure will have to be taken into account when planners make cost-benefit analyses for the proposed bicycle interventions (Mishan, et al., 2007).

According to literature, improved accessibility to transport infrastructure could raise the bid rent of individuals, because these transport facilities lower the cost to travel to a Central Business District (CBD) or because they reduce travel time. The bid rent is the maximum price a certain use is willing to pay to be located at a certain distance from the CBD of a city (Alonso, 1960). Because of rising transportation costs when you move further from the central city, in a hypothetical perfect situation, the bid rent decreases when moving further from the CBD. Planners generally agree that property prices increase with proximity to transportation facilities, because those facilities provide improved access to activity locations (Welch, et al., 2016).

Du & Mulley (2006) and Martínez & Viegas (2009) summarized multiple researches into the effect of increased accessibility on house prices. They found that most previous scientific studies that used a hedonic pricing method have found significant positive effects of improved accessibility on property values. However, there is great heterogeneity in used methods and used variables and there is spatial variation in effects. Overall, it can be stated that if a city invests in improved accessibility for its city dwellers, this leads to an increase in residential land value, with the size of this uplift depending on how far a property is located from the infrastructure (Mulley, 2013).

It is still unclear if the prior counts for bike infrastructure as well. Previous research on this matter is divided. Some researchers (e.g. Racca & Dhanju 2006; Shi, 2017) do find significant positive effects of bike lane proximity on house prices. Other researchers point at differences in the type of bike lane (e.g. Welch, et al., 2016; Krizek, 2006) and there is evidence for a different appreciation of bike infrastructure between inner-city dwellers and residents of suburbs (e.g. Mogush, et al., 2016), with the first group having a greater appreciation.

A possible drawback of being located close to bike infrastructure is the fact that most of this new bike infrastructure is placed on existing main roads in Paris. These main roads are already busy roads with lots of different types of traffic. New bikers will only add to this. Negative externalities, like traffic noise or air pollution, both during and after construction of the bike infrastructure, can negatively impact the property values and distort the possible positive effect of being closely positioned to bike infrastructure. Such negative effects have already been found by Kim, et al. (2007).

Existing literature is mostly focused on the American context, a context in which car-use is more prevalent and the use of a bike as a daily mode of transport is lower than in European cities (Buehler, 2010). New European research will be a necessary addition to existing research into the matter which is scarce, often not complete, or the effect of bike lanes is debated. New research, executed in the actual Parisian context could help Parisian city planners to better explain their investments in bike infrastructure in the city. This results in the main question of this research:

"What is the influence of the construction of new biking infrastructure on residential property prices in Paris, France?"

The research question has been made explicit in the conceptual model shown in **figure 2.** Structural, neighbourhood, transaction and locational attributes all influence residential property value. In this research, the influence of the locational attribute "distance to newly constructed bike lanes" (in green) on the property value (in blue) will be explored, using a difference-in-difference approach at five locations in Paris, France.

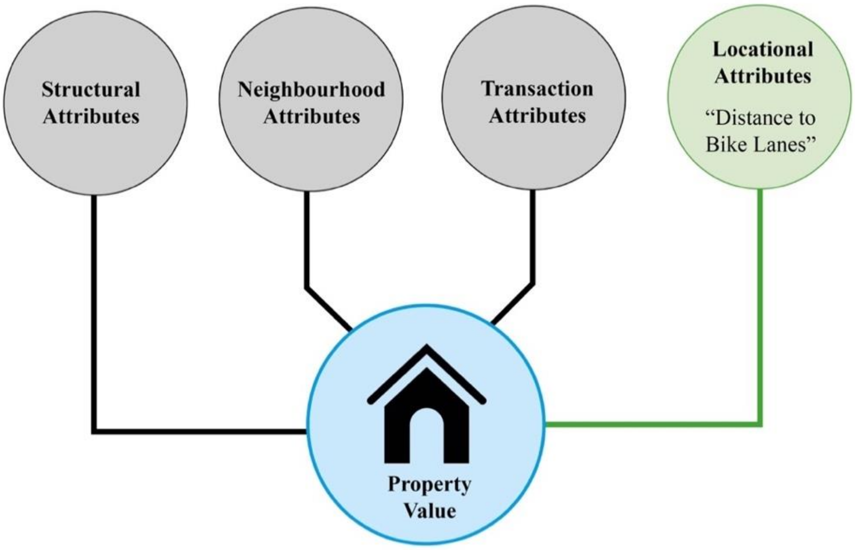

Figure 2: Conceptual model. Source: own work

The main question will be explored through four sub-questions that together answer the main question. Firstly, based on literature review, known external effects of bike infrastructure and their anticipated effects on property prices will be explored. This sub-question will stay qualitative, based on an analysis of existing literature on the matter. This results in the first sub-question:

1. *What external effects of bike lanes are known and in what ways could these external effects influence property values?*

Secondly, collected data from Paris, France will be researched through the programme STATA. The quantitative difference-in-difference approach will be used. The research will focus on five streets in Paris. Bike lanes were almost non-existent in the city of Paris until the early 2010s, which explains the focus on newly constructed bike lanes in this research. The five locations chosen for this research were some of the first streets in Paris that housed new bike lanes and meet the strict selection criteria for this research. Enough time has passed now after the construction of the bike lanes in these five locations to be able to investigate their treatment effects on surrounding house prices. For the second sub-question, the effect of the construction of nearby bike infrastructure on the dependent variable “transaction price” will be examined at the five locations in Paris.

2. *What is the found effect of proximate bike lane construction on property values in Paris, France?*

To gain even more insight into the effect of the construction of this bike infrastructure, in sub-question 3, it will be examined how the effect of the bike lane infrastructure changes over distance away from the bike infrastructure. This can be checked with an alternative model.

3. *How does this found effect change over distance to the bike lane infrastructure?*

Lastly, since Welch, et al. (2016) and Krizek (2006) found a different effect for different types of bicycle infrastructure, in sub-question 4, it will be examined whether a different effect of the bike lane infrastructure on property prices can be distinguished for different types of bike lanes. Two of the five streets in this research are part of the *Réseaux Express Vélo* (REV) system in Paris. In the last sub-question, it will be examined whether a difference in effect can be found between REV and non-REV bike lanes.

4. *Does the found effect differ between REV and non-REV bike lane infrastructure?*

The remainder of this thesis is structured as follows: in section 2, a literature review will explore the external effects of bike lanes and their possible effects on property values, as found in existing literature. Section 3 is dedicated to an explanation of the methodology and data collection of the thesis. The collected data is analysed and the results are explored and discussed in section 4, concluded by a conclusion in section 5 with recommendations for future research.

2] LITERATURE

Research into the effect of bike infrastructure on property values is still scarce. Most of the research has been carried out in cities in the United States of America. The majority of the studies known so far used hedonic pricing methods to investigate the influence of distance to bike paths on the price of properties. Known conclusions are summarized in **table 1**.

One existing research on property values and bicycle paths is executed by Racca & Dhanju (2006). In their analysis, using a hedonic pricing model, they looked at the impact of proximity to newly constructed bike paths on property prices in Delaware, USA. These bike paths were part of bigger city restructuring plans in the city of Dover, Delaware. The research spanned a dataset of 150,000 properties in the state of Delaware. Structural variables, like size and number of rooms were included in the regression as control variables. The variable of interest was a created dummy variable ‘proximity to a bike path’ that indicated whether a property was within a 50 metre range from the newly constructed bike paths or not. Properties within 50 meters of bike paths showed a positive significance (at the 1% level) of at least $8,800 and even higher when controlled for specific neighbourhood variables. Racca and Dhanju concluded that the bike paths had significant positive effects on the property prices in the state, due to their contribution to improved accessibility and their recreational value.

A similar research is executed by Shi (2017). Using a Hedonic Pricing Method, Shi investigated the impact of newly constructed bicycle paths on residential property prices in Portland, Oregon, USA.

Shi included transaction characteristics, property characteristics and neighbourhood characteristics in the regression. The variable of interest, however, was the distance to the nearest bike infrastructure in feet. Using a database of 17,163 transactions from Portland, Shi concluded that each quarter mile that a property was located away from the nearest bike infrastructure lowered the property prices with $66, indicating a preference of house buyers for high quality nearby bike infrastructure.

These first two studies show evidence for a positive effect of bike lanes on residential property prices. However, they do not use a difference-in-difference (DID) approach to investigate this effect. By including an analysis over time, a DID-approach can be used to explore whether the construction of the bike infrastructure has been responsible for the positive uplift of residential property prices around the new bike lanes. Kashian, et al. (2018) have applied a difference-in-difference approach in Muskego, Wisconsin, USA. Using a database of around 7,000 property transactions, the authors discovered that properties sold for a 8.6% higher transaction price in the period after completion of the Muskego bike path. This positive effect decreased over distance to the bike path. The study provides evidence that residents of Muskego saw the creation of the bike path as a positive development in their neighbourhood, one that added a premium to the price paid for sold residential properties after completion of the bike lane.

The found increase in house prices due to nearby biking infrastructure in these first studies could be attributed to multiple benefits of biking. Bullock, et al. (2016) summarize the five most important benefits of biking in their paper: *"(1) journey time savings, (2) convenience, (3) health benefits, (4) economic benefits and (5) reductions in motor vehicle use"* (p.1). Journey time saving is mostly caused by an improvement in the connection between the place of living, the place of work and transportation hubs between those places (Bullock, et al., 2016). It is the improved accessibility of the bike paths that is appreciated by city dwellers. Journey time savings are found to have a big wider economic benefit as well, since less time is spent in traffic jams.

Biking can improve health in the city in two ways: firstly, by increasing the physical activity of citizens, and secondly, by lowering the levels of air pollution, noise and congestion in the city, due to reductions in motorized vehicle use. This all contributes to increased liveability in the city (Teschke, et al., 2012). From a public health perspective, the construction of biking infrastructure is beneficial. According to Wang, et al. (2005), every 1 US$ investment in biking infrastructure means a direct medical benefit of 2.94 US$.

In contrast to aforementioned studies, Welch, et al. (2016) found different effects of bike lane proximity on house prices. The authors used a dataset of 146,311 transactions in Portland, Oregon, USA and applied a hedonic pricing model. Structural and neighbourhood characteristics were included as control variables in the model. The variable of interest was the distance to bike paths. The results were two-sided. Proximity to separated bike trails had a significant positive effect on house prices. However, if only looked at on-street bike lanes, proximity to the bike lane had a significant negative impact (1% significance) of $4541 on house prices. According to the authors, this was *"counterintuitive to prior findings in the literature"* (Welch, et al., 2016, p. 271). The positive effect of the accessibility benefit of being located closely to the bike infrastructure was wiped out by the negative effects (e.g., noise and air pollution) of living close to bike paths on major roads in these cases.

Research by Krizek (2006) supports these findings. Krizek investigated 35,002 transactions of residential properties in Minneapolis, Minnesota, USA. Krizek applied a hedonic pricing method to explore the effect of the variable 'distance to nearest bike lane' on residential property prices. Krizek distinguished roadside and non-roadside bicycle paths. Only roadside bike lanes significantly reduced the value of proximate residential properties, further strengthening the idea that on-road bike lanes lower the price of residential properties. Besides, according to Krizek, American citizens do often not consider bike lanes to be important amenities when they buy a house, which is mostly due to the low bike use for daily commute in the United States and the lack of existing proper bike infrastructure in American cities. Because of this low bike use, house buyers often do not acknowledge the improved accessibility that (new) bike lanes provide. That is why an effect of nearby bike infrastructure on house prices is oftentimes hard to find.

Lastly, the location of the bike infrastructure matters. Research by Connolly, et al. (2019) in Franklin County, Ohio, USA, included 21,133 observations. Structural and neighbourhood characteristics were included as control variables. The variable of interest was the distance to the nearest road bike facility. The authors concluded that the effect of bike infrastructure on residential property prices depends on the connectivity of the infrastructure. On-road bike facilities that were linked to local open space had a significant positive effect on residential property prices. However, on-road bike facilities connected to bus stops had an estimated capitalization effect of -$5,412.21 on property prices.

Mogush, et al. (2016) add that the effects of biking lanes changed when looking at the suburbs. In the suburbs, the found effect of bike lanes on property values was insignificant, compared to the significant positive effect in inner cities. There seems to be a difference in the appreciation of biking infrastructure between inner-city and suburban areas. Only in the inner cities, bike paths were seen as a positive asset when buying a house, most probably because of the shorter travel distances in compact inner cities.

Table 1: Summary of existing literature on bike infrastructure and its influence on real estate values**.**

Researchers	**Location**	**Impact of**	**Impact on**	**Findings***	**Significant?**	**Methods**
Racca & Dhanju (2006)	Delaware, USA	Proximity of bike path	Residential property values	+	Yes	Hedonic Pricing Method
Shi (2017)	Portland, Oregon, USA	Distance to nearest bike facility	Residential property values	+	Yes	Hedonic Pricing Method
Kashian, et al. (2018)	Muskego, Wisconsin, USA	Distance to newly constructed bike path (before and after completion)	Residential property values	+	Yes	Difference-in-Difference approach
Welch, et al. (2016)	Portland, Oregon, USA	Distance to biking facility	Residential property values	+ (separated bike trails) - (on-street bike lanes)	Yes Yes	Hedonic Pricing Method
Krizek (2006)	Minneapolis, Minnesota, USA	Distance to bike lanes	Residential property values	+ (nonroadside bike trails) - (roadside bike lanes)	Yes Yes	Hedonic Pricing Method
Connolly, et al. (2019)	Franklin County, Ohio, USA	Distance to biking facilities	Residential property values	+ (on-road bike facilities linked to local open space) - (on-road bike facilities close to bus stops)	Yes Yes	Hedonic Pricing Method
Mogush, et al. (2016)	Twin Cities Metropolitan Area, Minnesota, USA	Distance to bicycle facilities	Residential property values	+ (in the city) + (in the suburbs)	Yes No	Hedonic Pricing Method

*NOTE: +: Positive effect of bike lane proximity on house price, -: Negative effect of bike lane proximity on house price.

According to Stein (2010), this discrepancy might be due to a difference in lifestyle between inner cities and suburban areas. In American cities, the construction of biking infrastructure can help attracting the so-called 'creative class' to developments in the city. Real estate developers have learned that bike infrastructure can serve elite interests in the city and can steer gentrification of neighbourhoods, and thus the property values in those areas. For the Young Urban Professionals seeking for a house in the inner city, the proximity of bike infrastructure can indeed be seen as an advantage. Research by Flanagan, et al. (2016) confirms that in the American cities of Chicago and Portland, a bias exists of bike infrastructure investments in richer areas in the cities, with (pre)gentrification conditions.

As a concluding remark about the existing literature, it can be stated that the Hedonic Pricing Method is the most used method to examine the effect of the construction of bike paths on house prices. The difference-in-difference approach is, in contrast, scarcely used so far. Although oftentimes a significant and positive effect of bike infrastructure on housing prices is found, there seems to be a different effect for different locations and different types of bike lanes. All existing literature focuses on the American context as well, with European quantitative research missing.

The current thesis will fill the gap in existing literature by adding a difference-in-difference approach in the new European context of Paris, France. Because of the divergent results in previous literature, it is a challenge to draw up a fitting hypothesis for this study in Paris. Based on the scarce existing literature, it is hard to predict whether the effect on property prices of the bike lanes in Paris will be positive or negative. At the one hand, a significant positive effect of bike lane construction on residential property prices is to be expected in Paris, since bike use numbers in Paris are already up to 7% of daily commute (APUR, 2019), which is higher than in American cities (Buehler, 2010). Furthermore, the case of Paris concerns a compact inner city and according to Stein (2010), there is a bigger appreciation of bike lanes in compact inner cities. At the other hand, a significant negative effect of the new bike lanes could be expected in Paris, since the *Plan Vélo* focuses on constructing on-road bike lanes. Some previous studies in the USA (e.g. Connolly, et al. (2019)) have found a significant negative effect on property prices for these types of bike paths.

Either way, it is hard to predict whether a positive or negative effect is to be expected in Paris, certainly because no quantitative research on this topic has been carried out in Paris before. This research will fill this existing gap in literature. In the following section, an explanation of used data and methodology for this study will be given.

3] DATA AND METHODOLOGY

3.1] Empirical models

The methodology of this thesis is based on the pioneering work of Sherwin Rosen (1974) on hedonic pricing methods. By using a hedonic pricing formula, the effect of (a change in) one of the underlying characteristics on the property price can be examined. This is the key use of the hedonic pricing method in real estate (Monson, 2009) and can be applied to measure the effect of the construction of bike lanes on property values as well. The statistical technique that will be used is the difference-in-difference (DID) approach. In this method, the treatment effect of the construction of the bike lanes on the property prices in a target area can be compared to the change over time of the property prices in a control area, in order to see if there is a significant difference between the two areas after treatment.

The model specification used in this research is based on the difference-in-difference approaches used in research by Van Duijn, et al. (2016) and Liu & Liu (2020):

$$\ln(Transaction\ Price_{it}) = \alpha + \beta(Target_{it}) + \gamma(After_{it}) + \delta(Target_{it} * After_{it}) + \theta X_{it} + y_t + z_i + \varepsilon_{it} \qquad (1)$$

In **model 1**, the dependent variable is the natural logarithm of the transaction price for a residential property *i* in year *t*. α is the constant in the model and is included to assure linearity of the formula. $Target_{it}$ is a dummy variable that indicates whether a residential property is located in the target area of this research. If this variable equals 1, the property is located in the target area, otherwise the value is 0. β is the coefficient that captures the effect of being located in the target area of research on the transaction price. $After_{it}$ is a dummy variable that is 1 if a property was sold after completion of a proximate bike lane, otherwise the value is 0. γ is the coefficient that captures this effect. An interaction variable is created by multiplying $Target_{it}$ and $After_{it}$. This interaction is the variable of interest of this thesis and represents the effect of bike lane construction on property prices in the target area. δ is the coefficient that captures this effect. X_{it} represents all the structural, neighbourhood and locational characteristics that are included in the regression as control variables. θ represents a vector of coefficients of these control variables. y_t indicates year fixed effects and z_i indicates zip code fixed effects. ε_{it} is the error term of the model. β, γ, δ and θ are the coefficients that will be estimated in the regression.

The target area of this research is designed to be an Euclidean circle of 50 metres around the newly constructed bike lanes. Bike lanes have a relatively small catchment area and according to literature their effects on house prices do not reach far. The distance of 50 metres is based on earlier studies by Racca & Dhanju (2006) and Shi (2017) where a target area of 50 metres around bike infrastructure was used as well and proved to be correct. Furthermore, a sensitivity test has been carried out with varying sizes of target and control areas[1]. It seemed that no effect dominated for most of the

[1] For this sensitivity analysis, experimental regressions were carried out for target area sizes of 0-50m; 0-75m; 0-100m; 0-150m; 0-250m; 0-500m; and 0-1000m, with corresponding control area sizes of 50-100m and 200-250m; 75-150m; 100-200m; 150-300m; 250-500m; 500-1000m; and 1000-2000m, respectively.

other choices of target and control areas. Based on these experiments with different target and control areas and the literature, it was chosen to stick to the target area size of 50 metres. For same reasons, the control area was chosen to be a circle of residential properties located between 50 and 100 metres away from the bike infrastructure. It is expected that the treatment effect of the new bike lanes can only be found in the target area and not in the control area. The target and control areas in this research are relatively small and located next to each other. This makes them well suited for a comparison, since the houses in both the target and control area will be similar and will have similar neighbourhood characteristics.

Furthermore, the data set is split in a group before and after the construction of the bike lanes. Whether a property was sold after start of the construction of the bike infrastructure is indicated by the dummy ‘After’. The first day of construction for each bike lane location is taken as the date to split the data in these two groups. It is chosen to work with the first day of construction and not completion, because in this way, potential anticipation effects can be taken into account in the ‘after’ period as well.

Lastly, an alternative model is designed. **Model 1** treats the entire target area as being homogeneous. However, there can be variations in the effect of nearby bike lanes on property prices inside the target area. Based on previous literature, for example, it is to be expected that the effect of bike lanes decreases with rising distance to the bike lanes. To be able to measure this changing effect, different distance classes to the bike lanes have been designed, in steps of 10 metres. In this way, the target area of 50 metres around the bike lanes is divided into five distance rings. This alternative model can be found in **model 2**:

$$\ln(Transaction\ Price_{it}) = \alpha + \beta(After_{it}) + \gamma(Distance(0-10m)_{it} * After_{it}) + \delta(Distance(10-20m)_{it} * After_{it}) + \varphi(Distance(20-30m)_{it} * After_{it}) + \mu(Distance(30-40m)_{it} * After_{it}) + \rho(Distance(40-50m)_{it} * After_{it}) + \theta X_{it} + y_t + z_i + \varepsilon_{it} \quad (2)$$

This alternative model is similar to **model 1**, but this time more interaction variables are included. Every interaction variable represents the interaction between the dummy ‘After’ and a distance ring. Because the target area is divided into five distance rings, there are five interaction variables here as well. This alternative model will help finding differences inside the target area of this research. The coefficients that need to be estimated in the alternative model are β, γ, δ, φ, μ, ρ and θ.

3.2] Data collection

For the difference-in-difference approach of this research, data for Paris are collected from various different sources.

Five bike lane locations were chosen as focus areas for this research. Investigating multiple locations in Paris will help generalizing the found effect for the whole city. The five chosen locations for this research are: ‘Boulevard Voltaire’, ‘Boulevard de Sébastopol’, ‘Avenue de Flandre’, ‘Rue Lecourbe’ and ‘Boulevard Arago’. An overview of these five locations can be found in **table 2.** Maps with the location, target and control areas for these five streets can be found in **appendix A.** Finding enough locations for this research was a challenge, because the locations had to meet three strict criteria to be of use for this research. Firstly, enough time must have passed after construction of the bike lane to investigate the effects of the new bike infrastructure on surrounding property prices after completion. Bike lanes constructed in 2019 or later could therefore not be used in this study. Secondly, the bike lanes must be situated in the middle of residential neighbourhoods in Paris to ensure that there are enough surrounding residential properties to use for the research. Lastly, the chosen streets should not be at famous landmarks in Paris, (like the Champs Élysées or Rue de Rivoli) because it was feared that the touristic uses of those streets could disturb the effect. The five locations chosen for this research did meet these strict requirements. It is important to note that it is expected that the chosen locations are quite endogenous.

Information about the new bike infrastructure in Paris was downloaded from the *‘Observatoire du plan vélo’* (https://planvelo.paris/) and included in **table 2**. The locations of the bike lanes could be downloaded as a Shapefile and displayed on a map via the programme ArcMAP. From these five locations, the ‘Boulevard Voltaire’ and ‘Boulevard de Sébastopol’ are part of the bigger REV network and serve as main bike routes in the city of Paris. The other three locations house ‘regular’ bike infrastructure. A complete map of the *Plan Vélo* can be found in **figure 3**. The network of REVs is indicated in pink on the map of the *Plan Vélo*. The five locations of interest for this research are labelled and indicated in red in **figure 3.** The difference-in-difference approach applied in this research will focus on these five locations.

Table 2: Overview of the five locations in this research. Source: own work.

Name location	Description of bike lane	REV	Start construction	End construction
Boulevard Voltaire	Protected REV one-way bike paths on both sides of the road.	Yes	1 July 2017	1 June 2018
Boulevard de Sébastopol	Protected REV two-way bike path in the middle of the road.	Yes	1 May 2018	1 November 2018
Avenue de Flandre	One-way bike paths on both sides of the road.	No	1 January 2018	1 June 2018
Rue Lecourbe	Protected one-way bike paths on both sides of the road	No	1 May 2018	1 November 2018
Boulevard Arago	One-way bike paths on both sides of the road	No	6 February 2017	31 March 2017

Structural data about the residential properties are publicly available for the whole of France on the website https://www.data.gouv.fr/fr/datasets/demandes-de-valeurs-foncieres-geolocalisees/#_. The used governmental database provides an overview of all residential property transactions in central Paris (*Departément 75*) between 2014 and 2019. The dataset provides information about the address of the properties, zip code, the date of transfer, the transaction price (€), size of the real estate and the lot (m^2)

and the number of rooms. Herath & Maier (2010) note that structural attributes like these can be found as control variables in almost every hedonic pricing research in real estate studies, because the structural attributes of a property are important determinants of the house price. Zip codes are included in the research to control for fixed effects related to the location of a property. In this way, we can control for houses within the same zip code that might be correlated to each other. (Mummolo & Peterson, 2018). Year fixed effects are included for this reason as well. The properties from this database were located on the map of Paris in ArcMAP by using their coordinates. The distance to every bike lane location was calculated using the 'Near' function.

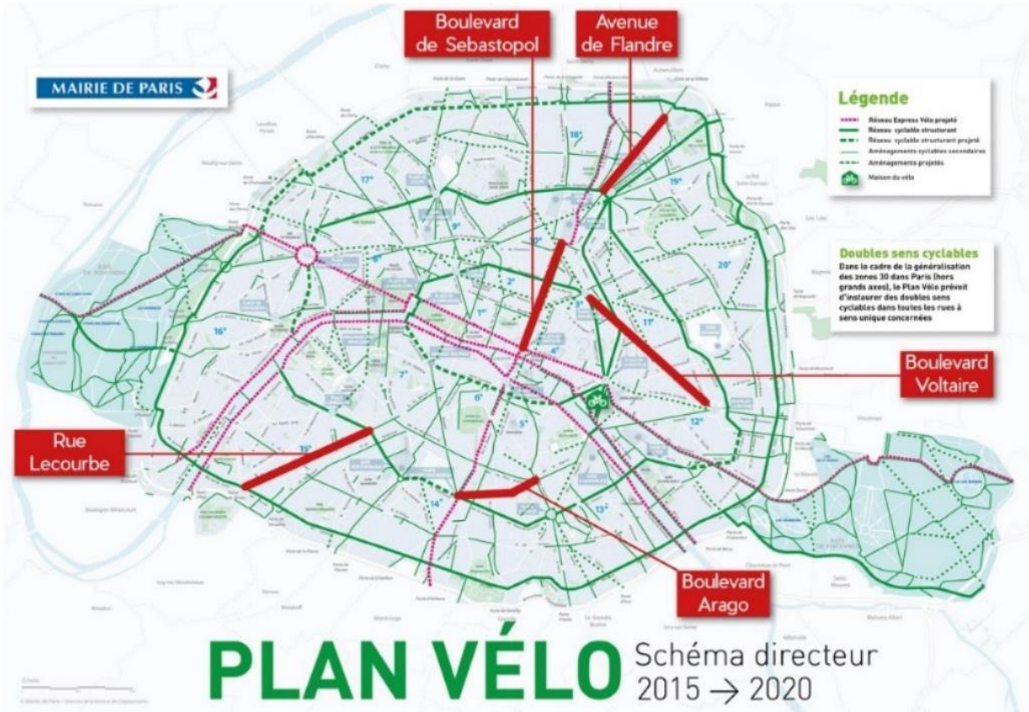

Figure 3: The *Plan Vélo* for Paris as envisioned between 2015-2020. REVs are indicated in pink. The streets that are the focus of this research are shown in red. Source: Mairie de Paris, 2015 and own edit.

The price of a property is influenced by attributes in the neighbourhood as well. Neighbourhood data are collected as control variables from the website of APUR (*Atelier Parisien d'Urbanisme)*, a Parisian Statistics Bureau. They have been collecting data for Paris for about 50 years and have displayed the data in an open geo-data platform on the website: https://www.opendata.apur.org/. Data are collected about the percentage of immigrants, the share of single households, education levels, unemployment numbers and the share of car and bike users in every neighbourhood. In ArcMAP, these neighbourhood data are added to the property data by using the 'Spatial Join' function. In ArcMAP, distances from every property to the nearest metro station are calculated as well using the 'Near' function. This variable is also included as a control variable.

All collected data were joined in one table and processed in the statistics software STATA. Missing data, outliers and duplicates were removed from the data set. The whole STATA Syntax can be found in **appendix B**. Furthermore, the dummies 'After' and 'Target_50m' were created and an interaction variable of these two. Histograms were made to check all variables for normality. The histograms can be found in **appendix C**. Variables that were not normally divided were transformed using a log-function in STATA to improve their normality. This modification removes the skewness of the variables and makes them better suited to use for regression analysis.

Now that all necessary variables have been generated, the descriptive statistics of all variables can be found in **table 3**. The full sample of the five locations contains 6,741 observations of individually sold properties in the French city of Paris. All these properties were sold between 2014 and 2019 and are situated at most 100 metres away from one of the five locations of interest. The dependent variable of this research is the (natural logarithm of the) transaction price. The mean transaction price in the areas of research between 2014 and 2019 was €440,000. The average transacted property has 2.4 rooms and a real estate surface of 50.3 m^2. The average unemployment percentage in the sample is 11.1%, 63.4% of residents have not attended university, 19.7% of residents are immigrants, 52.3% of inhabitants are single households, 9.8% use a bike for daily commute to work, 10.0% use a car for daily commute. The average distance to the nearest metro station is 193.7 metres and to the nearest bike lane is 58.1 metres.

Table 3: Descriptive Statistics of the full sample

Variable	Mean	Std.Dev.	Min	Max	Source
Structural characteristics					
Transaction Price (€)	440000	275000	30000	1890000	Data.gouv.fr
Real Estate Surface (m^2)	50.28	27.535	15	200	Data.gouv.fr
Number of Rooms	2.391	1.093	1	6	Data.gouv.fr
Zip Code	75011.78	4.571	75001	75019	Data.gouv.fr
Year	2016.502	1.618	2014	2019	Data.gouv.fr
Neighbourhood characteristics					
Unemployment (%)	11.093	3.102	5.794	23.501	APUR
No Higher Education (%)	63.415	8.058	27.097	75.976	APUR
Immigrants (%)	19.654	5.353	11.618	38.238	APUR
Singles (%)	52.302	5.473	30.758	68.2	APUR
Bike Users (%)	9.758	2.381	3.96	16.331	APUR
Car Users (%)	10.04	4.385	3.132	23.602	APUR
Locational characteristics					
Distance to metro (m)	193.725	101.096	4.851	557.888	ArcMAP calculation
Distance to bike lane (m)	58.085	22.926	9.393	99.981	ArcMAP calculation
Dummy variables					
After (1 = yes)	.339	.473	0	1	
Target (50m) (1 = yes)	.409	.492	0	1	
Interaction After * Target (50m)	.138	.345	0	1	
Observations	6741				

Lastly, there are five OLS assumptions that need to be tested in order to ensure that the coefficient estimates from the regressions and the associated standard errors are valid. If these five assumptions are met, the models can be seen as being BLUE: Best Linear Unbiased Estimator (Brooks and Tsolacos, 2010), which means that there is an unbiased prediction of the coefficients in the models.

The results of the testing of the five assumptions in this research can be found in **appendix D**. Linearity can be assured by adding a constant to the regressions. Autocorrelation is checked via a correlation matrix and a VIF-analysis. Because the sample size of this research is sufficiently large, violation of the normality assumption is virtually inconsequential. Found heteroskedasticity in this research is addressed by using robust standard errors in the models. By applying these modifications to the regressions, no further issues related to assumption violations are expected and the research can be carried out and results are to be discussed in the following section.

4] RESULTS AND DISCUSSION

4.1] Graphical Exploration

Firstly, a graphical exploration of transaction prices around newly constructed bike infrastructure in the five locations is carried out. Average transaction prices per year are calculated for the five areas of this research. The results are displayed in the graph in **figure 4.** It is visible that in all areas, there has been a slight uplift in the average transaction price over the years.

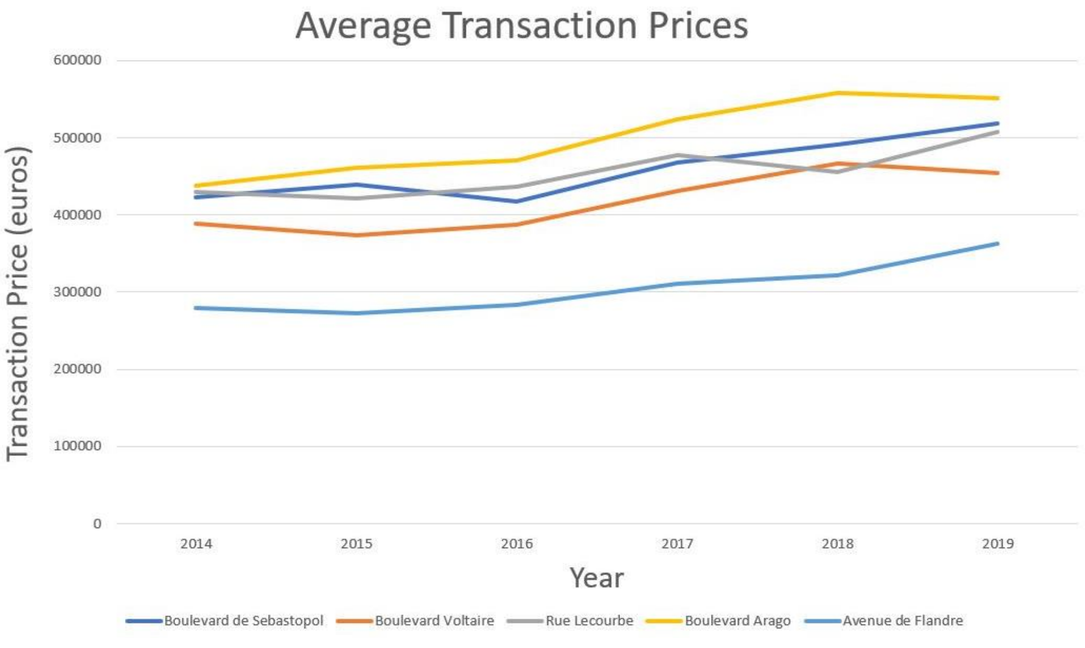

Figure 4: Average transaction price in euros per year for the areas of 100 metres around the bike lanes. Source: own work in Excel, based on own calculations.

In figure 5, average transaction prices over time for the target and control areas of all locations together are shown. It seems that in 2014 and 2015, average transaction prices in both the target and control areas were almost equal. However, from 2016 onwards, it seems that the uplift in average transaction prices in the target area of this research is bigger than in the control area. A statistical test will now explore whether the bigger uplift in transaction price in the target area can be attributed to the construction of nearby bike infrastructure.

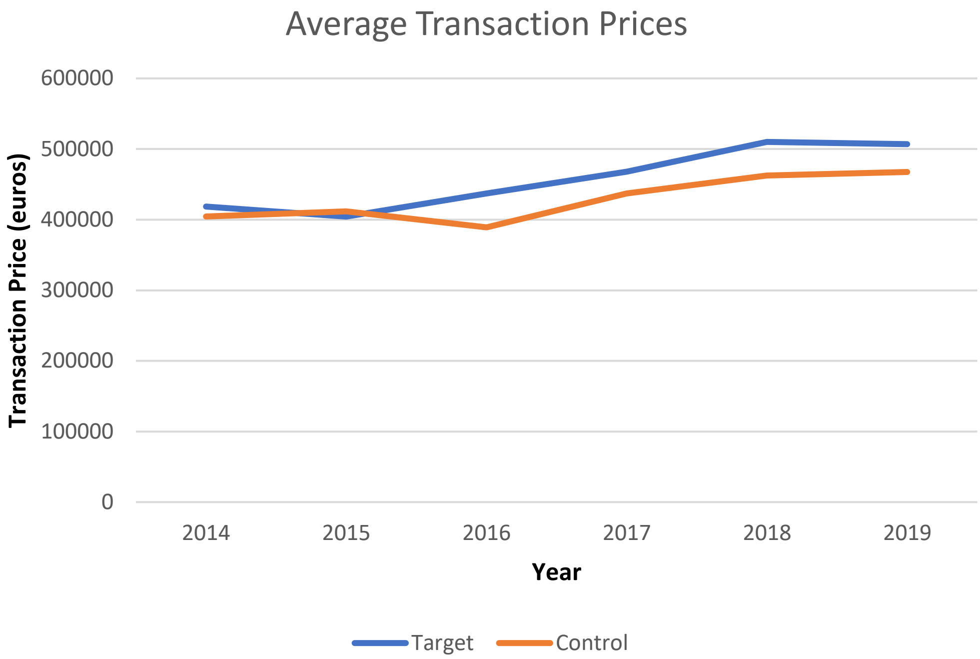

Figure 5: Average transaction price in euros per year for the target and control areas of this research. Source: own work in Excel, based on own calculations.

4.2] Regression results

The results of the regressions executed in this thesis can be found in **table 4**. Full regression outcomes can be found in **appendix E**. First, the difference-in-difference approach is applied to the full sample. In column (1), only the variable of interest and zip code and year fixed effects are included in this regression. The control variables (neighbourhood, structural and locational attributes) are not included. It seems that this model has a low R^2 of 0.080, meaning that only 8% of the variance in the dependent variable *ln(Transaction Price)* can be explained by the model. It seems that the variable of interest *"After * Target(50m)"* has an insignificant effect on the dependent variable. In column (2), all control variables are added to the regression. The R^2 is now 0.763, indicating a better model fit. However, in this regression too, the effect of the variable of interest on the natural logarithm of the transaction price is insignificant. This means that no significant effect of bike lane construction on surrounding property prices in the target area can be found in the full sample. The uplift in property prices as shown in **figure 5** cannot be attributed to the construction of nearby bike lanes.

It could, however, be that there is heterogeneity between different kinds of bike lanes. Two of the five bike lanes in this research are part of the bigger REV network. It could be that the more extensive network of those bike lanes and the larger volume of users causes the REV bike paths to have a significant effect on property prices. That is why in column (3) and (4), the regressions are executed again, but this time only for the REV locations (Boulevard Voltaire and Boulevard de Sébastopol). The R^2 in column (3) and (4) are comparable to the ones in column (1) and (2). It seems that also for REV bike lanes only, the treatment effect of bike lane construction on property prices is insignificant.

Table 4: Difference-in-Difference Regression Outcomes

	Full Sample	Full Sample	REV Only	REV Only
	(1)	(2)	(3)	(4)
VARIABLES	ln(Transaction Price)	ln(Transaction Price)	ln(Transaction Price)	ln(Transaction Price)
After * Target(50m)	0.000361	0.00340	-0.0263	0.0112
	(0.0313)	(0.0159)	(0.0443)	(0.0220)
Structural characteristics (2)	NO	YES	NO	YES
Neighbourhood characteristics (6)	NO	YES	NO	YES
Locational characteristics (1)	NO	YES	NO	YES
Zip Code Fixed Effects (10)	YES	YES	YES	YES
Year Fixed Effects (5)	YES	YES	YES	YES
Constant	13.31***	8.421***	12.82***	9.714***
	(0.280)	(0.346)	(0.0511)	(0.824)
Observations	6,741	6,741	3,594	3,594
R-squared	0.080	0.763	0.042	0.750

NOTE: The dependent variable is ln(Transaction Price). Sample size is < 100m; target area is 50m; control area is 100m. Robust standard errors can be found in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The found insignificant effect of bike lane construction on property prices is not entirely in line with conclusions from previous literature. In contrast to previous research in the USA (Racca & Dhanju (2006); Shi, (2017)) where either a significant positive effect or negative effect of bike lane proximity was found, this research has found no significant impact at all. There are two ways to look at these insignificant results. At the one hand, these results show at least that there is no significant negative effect of bike lane construction on property prices. This means that Parisian house prices were not influenced by any negative externalities (like noise pollution or other nuisances) after construction of the bike lanes: house buyers did not see the newly constructed bike lanes as a reason to pay a lower price for a nearby house. At the other hand, the insignificant results show that there is no positive effect of the bike lanes on house prices as well. This means that the benefits of the bike trails and biking are not clear to the Parisian house buyers. Probably, this is due to the low use of bikes for daily commute. House buyers simply do not appreciate nearby bike lanes, because they do not use them themselves. The possibility that the non-significant effect is caused because the control area of 50-100 metres is also part of the treated area is small. In the sensitivity test, no such treatment effect in the control area was found.

A possible explanation for the differences between the results of this research and the significant positive effect found in some American literature is that in the American context, bike paths more often served a recreational purpose or were part of city renewal plans. Newly constructed bike trails in the cities of Portland (Welch, et al., 2016) or Twin Cities (Mogush, et al., 2016), for example, were laid down in attractive green spaces or were part of extensive redevelopment projects. This could be the reason why a significant positive effect of these bike trails was found in the American context, but not in the Parisian context with on-street bike lanes, where the new bike lanes in Paris serve more a function of a daily mode of commute than a recreational purpose and were laid down on already existing commuter streets. Apparently, the addition of the bike lanes on Parisian streets has almost been unnoticed by Parisian house buyers in the surrounding neighbourhoods.

Even though a non-significant effect has been found so far, in **table 5**, the alternative model can be found. In this model, it is checked whether the non-significant effect found so far sustains over different distance rings to the bike lanes. In total, five dummies have been created for different distances away from the bike infrastructure (in steps of ten metres). Five interaction variables have been created with the dummy *'After'* and are included in the regression. In this alternative model, it seems that indeed for all distance classes in the target area, there is an insignificant effect of proximate bike lane construction on property prices. Effects are insignificant for all distances away from the bike lane and the insignificance is thus homogeneous for the entire target area. The effect in the class *"After * Distance(0-10m)"* has been omitted because of the low number of observations in this class. One thing that is interesting to note about the estimated coefficients is that there is a trend visible in the found insignificant effects. For the class *"After * Distance(10-20m)",* the found effect is $((\exp^{0.0443} -1)*100\%$ =) plus 4.5% on the property price, but moving away from the newly constructed bike infrastructure, this effect decreases to plus 1.3% for the distance class 40-50 metres away from the new bike lanes. Even though these effects are not significant, this decreasing trend is visible and it is worth to note this.

Table 5: Alternative model specification

VARIABLES	(5) ln(Transaction Price)
After * Distance (0-10m)	-
After * Distance (10-20m)	0.0443
	(0.0295)
After * Distance (20-30m)	0.0317
	(0.0151)
After * Distance (30-40m)	-0.00294
	(0.0213)
After * Distance (40-50m)	0.0134
	(0.0197)
Structural characteristics (2)	YES
Neighbourhood characteristics (6)	YES
Locational characteristics (1)	YES
Zip Code Fixed Effects (10)	YES
Year Fixed Effects (5)	YES
Constant	8.429***
	(0.345)
Observations	6,741
R-squared	0.763

NOTE: The dependent variable is ln(Transaction Price).
Robust standard errors can be found in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1

The clear non-existent effect of bike lane construction on property prices will concern Parisian policy makers responsible for constructing bike infrastructure in the city. Apparently, house buyers in Paris do not consider nearby bike paths as an important asset when buying a house, one that could raise the price paid for the property. This could make it harder for policy makers to stress the welfare benefits of bike lanes in their cost-benefit analyses. This study shows that the construction of nearby bike lanes and their benefits go almost unnoticed to nearby Parisian house buyers. This was also the number one conclusion of Copenhagenize (2019) when they stated that extra communications about the benefits of biking were necessary in Paris to make Parisians aware of the benefits of biking in the city. A similar conclusion was also stressed by Krizek (2006) who stated that Americans do not consider bike lanes to be important amenities when buying a house, which made it hard to find an effect of newly constructed bike lanes on property prices. Clearly, right now the benefits of having a bike lane close to your house are not evident enough to Parisians. Perhaps the appreciation of nearby bike lanes could change in the future if bike use numbers in Paris increase as a result of the expansion of the bike infrastructure. Clear marketing campaigns about the benefits of biking for Parisians could help spread this message as well.

5] CONCLUSION

The aim of this research was to answer four sub-questions in order to respond to the main question *"What is the influence of the construction of new biking infrastructure on residential property prices in Paris, France?".*

By applying a difference-in-difference approach at five locations in Paris, France, this research has statistically shown that there is no significant effect of newly constructed bike lanes on surrounding residential property prices in the city. The study spanned a database of 6.741 observations divided over a target area of 50 metres and a control area of 50-100 metres. The insignificant effect persisted over distance away from the bike infrastructure and was found for both REV and non-REV bike lanes. The results show that Parisian house buyers do not consider nearby bike lanes to be important assets when buying a house. The study proposes that city planners involved with bike infrastructure planning in Paris should invest more time and money in clear communications about the welfare benefits of cycling in the city.

One implication of this research was that the bike infrastructure in Paris is still relatively new. Data on property prices were only available between 2014 and 2019. Bike path construction in Paris only started to accelerate in the mid-2010s. This means that the dummy 'After' in the difference-in-difference approach in this thesis only consisted of transaction data from a relatively short period after completion of the bike infrastructure. It is recommended that this research will be replicated later in the future to be able to investigate a longer period after the construction of the bike infrastructure. Such research could check whether the insignificant effect after construction found in this research persists over a longer time period as well.

Furthermore, in the future, more locations in Paris where bike infrastructure has been constructed could be investigated. In 2019, the city of Paris added a record amount of bike infrastructure to the city. In a few years from now, it will be possible to check whether the found insignificant effect can also be found at more places in Paris. Adding more research locations (and thus observations) to the five locations of this study will help to get a stronger prove for generalization of the found effect.

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7] APPENDICES

APPENDIX A | LOCATIONS WITH TARGET AND CONTROL AREAS

The five maps below show the five locations of focus of this research. In every map, the constructed bike infrastructure is indicated with a red line. The target area (50m) is shown with orange dots. The control area (50m-100m) is shown with blue dots. Source of the maps: own work in ArcMAP.

Figure A.1: Boulevard Voltaire

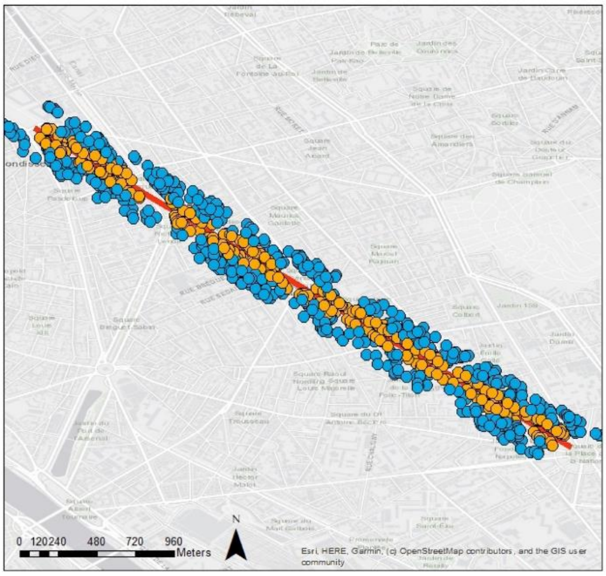


Figure A.2: Boulevard de Sébastopol

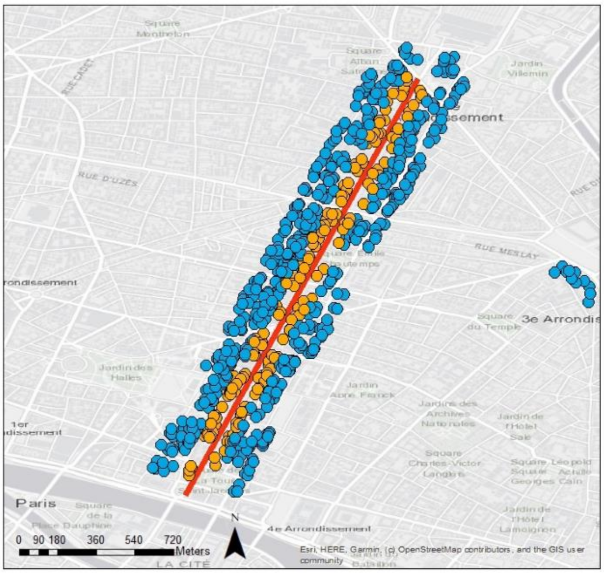
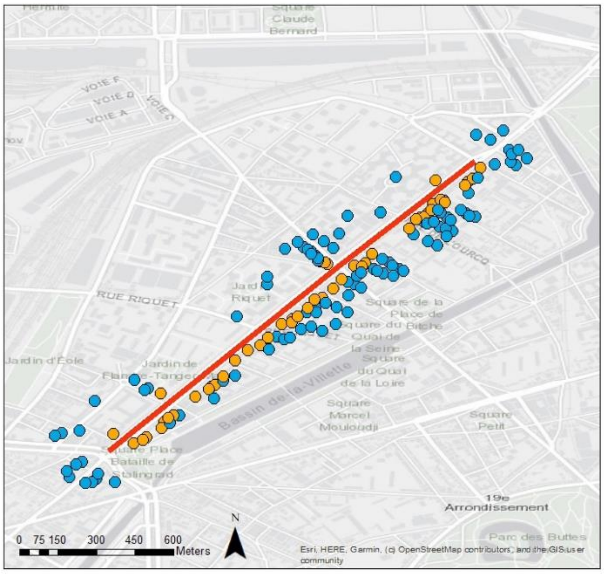


Figure A.3: Rue LeCourbe

Figure A.4: Boulevard Arago

Figure A.5: Avenue de Flandre



APPENDIX B | STATA SYNTAX

Import the dataset as a csv-file

import delimited "C:\Users\mauri\Desktop\ParijsAlleVariabelen29nov.csv"

Drop variables that are not necessary

drop objectid join_count target_fid join_count_1 target_fid_1 join_count_12 target_fid_12 join_count_12_13 target_fid_12_13 numero_dis ancien_nom ancien_id_ numero_vol lot1_numer lot1_surfa lot2_numer lot2_surfa lot3_numer lot3_surfa lot4_numer lot4_surfa lot5_numer lot5_surfa code_natur nature_cul code_nat_1 nature_c_1 near_fid ancien_cod

Destring variables to make them numeric

destring transactio real_surfa rooms_nr terrain_su longitude latitude unemployme no_higher_ immigrants singles_pc dist_bike near_dist pct_acto_2 pct_acto_3, replace force dpcomma

Rename variables

rename mutation_i mutation_id

rename mutation_d mutation_date

rename mutation_n mutation_nature

rename transactio transaction_price

rename address_su address_subnr

rename address_na address_name

rename address_co address_code

rename commune_co commune_code

rename commune_na commune_name

rename function_c function_code

rename real_surfa real_surface

rename terrain_su terrain_surface

rename unemployme unemployment_pct

rename no_higher_ no_higher_edu_pct

rename immigrants immigrants_pct

rename singles_pc singles_pct

rename near_dist dist_metro

rename pct_acto_2 bike_users_pct

rename pct_acto_3 car_users_pct

Label variables

label variable mutation_id "Mutation ID

label variable mutation_date "Mutation Date

label variable mutation_nature "Mutation Type

label variable address_nr "Address Number

label variable address_subnr "Address Subnumber

label variable address_name "Address Name

label variable address_code "Address Code

label variable commune_code "Commune Code

label variable commune_name "Commune Name

label variable department "Department

label variable lot_id "Lot ID

label variable lot_nr "Lot Number

label variable longitude "Longitude

label variable latitude "Latitude

label variable transaction_price "Transaction Price

label variable zip_code "Zip Code

label variable function_code "Function Code

label variable function "Function

label variable real_surface "Real Estate Surface

label variable rooms_nr "Number of Rooms

label variable terrain_surface "Lot Size

label variable unemployment_pct "Unemployment (%)

label variable no_higher_edu_pct "Nog Higher Education (%)

label variable no_higher_edu_pct "No Higher Education (%)

label variable immigrants_pct "Immigrants (%)

label variable singles_pct "Singles (%)

label variable bike_users_pct "Bike Users (%)

label variable car_users_pct "Car Users (%)

label variable dist_metro "Distance to Metro (m)

label variable dist_bike "Distance to Bike Lane (m)

label variable location "Location

Order variables

order mutation_id mutation_date mutation_nature address_nr address_subnr address_name address_code commune_code commune_name department lot_id lot_nr longitude latitude transaction_price zip_code function_code function real_surface rooms_nr terrain_surface unemployment_pct no_higher_edu_pct immigrants_pct singles_pct bike_users_pct car_users_pct dist_metro dist_bike location

Drop commercial and industrial buildings and dépendences

sum function_code, detail

drop if function_code == 3

drop if function_code == 4

drop if function_code == 0

drop if function_code == .

Drop duplicates

duplicates report mutation_id

duplicates tag mutation_id, generate (duplicates_mutation_id)

label variable duplicates_mutation_id "Duplicates Mutation ID

keep if duplicates_mutation_id == 0

Drop outliers in transaction prices

sum transaction_price, detail

keep if inrange(transaction_price, r(p1), r(p99))

drop if transaction_price == 0

drop if transaction_price == .

Drop missing real estate surfaces and surfaces smaller than 15 m^2 and bigger than 200 m^2

```
sum real_surface, detail
drop if real_surface == 0
drop if real_surface == .
drop if real_surface <15
drop if real_surface >200
```

Drop missing room number data and properties with more than six rooms

```
sum rooms_nr, detail
drop if rooms_nr == 0
drop if rooms_nr == .
drop if rooms_nr >6
```

Drop other missing data

```
drop if zip_code == 0
drop if zip_code == .
drop if longitude == .
drop if longitude == 0
drop if latitude == .
drop if latitude == 0
drop if unemployment_pct == 0
drop if unemployment_pct == .
drop if no_higher_edu_pct == 0
drop if no_higher_edu_pct == .
drop if immigrants_pct == 0
drop if immigrants_pct == .
drop if singles_pct == 0
drop if singles_pct == .
drop if bike_users_pct == 0
drop if bike_users_pct == .
drop if car_users_pct == 0
drop if car_users_pct == .
```

Drop missing distances and distances to bike lanes bigger than 100 metres

```
drop if dist_metro <=0
drop if dist_metro == .
drop if dist_bike <= 0
drop if dist_bike == .
drop if dist_bike >100
```

Generate dates

```
gen new_date = date(mutation_date,"DMYhms")
format new_date %td
label variable new_date "Formatted Date
```

Generate year variable

```
gen year = year(new_date)
label variable year "Year
```

Generate dummy variable ‘After’

```
gen after = 0
replace after = 1 if location =="Boulevard Voltaire" & new_date>date("20170701","YMD")
replace after = 1 if location == "Boulevard de Sébastopol" & new_date>date("20180501","YMD")
replace after = 1 if location =="Rue LeCourbe" & new_date>date("20180501","YMD")
replace after = 1 if location=="Boulevard de Arago" & new_date>date("20170206","YMD")
replace after = 1 if location=="Avenue de Flandre" & new_date>date("20180101","YMD")
label variable after "After
```

Generate dummy variable ‘Target’

```
gen target_50m = 0
replace target_50m = 1 if dist_bike <=50
label variable target_50m "Target (50m)
```

Generate interaction variable 'Target x After'

gen after_x_target50m = after* target_50m

label variable after_x_target50m "Interaction After & Target(50m)

Install outreg2 and asdoc

ssc install outreg2

ssc install asdoc

Make histograms, check for normality and transform variables into log-functions

hist transaction_price

gen log_transaction_price = log(transaction_price)

label variable log_transaction_price "ln(Transaction Price)

hist log_transaction_price

hist real_surface

gen log_real_surface = log(real_surface)

label variable log_real_surface "ln(Real Estate Surface)

hist log_real_surface

hist rooms_nr

hist unemployment_pct

gen log_unemployment_pct = log(unemployment_pct)

label variable log_unemployment_pct "ln(Unemployment (%))

hist log_unemployment_pct

hist no_higher_edu_pct

gen log_education_pct = log(no_higher_edu_pct)

label variable log_education_pct "ln(Education (%))

hist log_education_pct

hist immigrants_pct

gen log_immigrants_pct = log(immigrants_pct)

label variable log_immigrants_pct "ln(Immigrants (%))

hist log_immigrants_pct

hist singles_pct

gen log_singles_pct = log(singles_pct)

```
label variable log_singles_pct "ln(Singles (%))
hist log_singles_pct
hist bike_users_pct
gen log_bike_users = log( bike_users_pct)
label variable log_bike_users "ln(Bike Users (%))
hist log_bike_users
hist car_users_pct
gen log_car_users = log( car_users_pct)
label variable log_car_users "ln(Car Users (%))
hist log_car_users
hist dist_metro
gen log_dist_metro = log(dist_metro)
label variable log_dist_metro "ln(Distance to Metro)
hist log_dist_metro
hist dist_bike
gen log_dist_bike = log( dist_bike)
label variable log_dist_bike "ln(Distance to Bike)
hist log_dist_bike
```

Generate dummy variables distances

```
gen dist_0_10 = 0
replace dist_0_10 = 1 if dist_bike >0 & dist_bike <=10
gen dist_10_20 = 0
replace dist_10_20 = 1 if dist_bike >10 & dist_bike <=20
gen dist_20_30 = 0
replace dist_20_30 = 1 if dist_bike>20 & dist_bike<=30
gen dist_30_40 = 0
replace dist_30_40 = 1 if dist_bike>30 & dist_bike<=40
gen dist_40_50 = 0
replace dist_40_50 = 1 if dist_bike>40 & dist_bike<=50
```

Descriptive Statistics

summarize transaction_price real_surface rooms_nr zip_code year unemployment_pct no_higher_edu_pct immigrants_pct singles_pct bike_users_pct car_users_pct dist_metro dist_bike after target_50m after_x_target50m

Assumption Testing

Assumption 2: Homoscedasticity

reg log_transaction_price log_real_surface rooms_nr i.year i.zip_code i.function_code log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users log_car_users log_dist_metro after target_50m after_x_target50m

rvfplot, yline(0)

estat hettest

Assumption 3: No autocorrelation

Correlation Matrix

corr log_transaction_price log_real_surface rooms_nr zip_code year log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users log_car_users log_dist_metro log_dist_bike after target_50m after_x_target50m

VIF-Analysis

reg log_transaction_price log_real_surface rooms_nr i.year i.zip_code i.function_code log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users log_car_users log_dist_metro after target_50m after_x_target50m

estat vif

Assumption 5: Normality of the error terms

reg log_transaction_price log_real_surface rooms_nr i.year i.zip_code i.function_code log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users log_car_users log_dist_metro after target_50m after_x_target50m

predict r, resid

kdensity r, normal

pnorm r

hist r, normal

Regression Models

Regression Model 1: Base model

reg log_transaction_price i.year i.zip_code i.function_code after target_50m after_x_target50m, robust

Regression Model 2: Base model + control variables

```
reg log_transaction_price log_real_surface rooms_nr i.year i.zip_code i.function_code
log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users
log_car_users log_dist_metro after target_50m after_x_target50m, robust
```

Alternative model (model 5)

```
gen after_x_dist_0_10 = after*dist_0_10

gen after_x_dist_10_20 = after*dist_10_20

gen after_x_dist_20_30 = after*dist_20_30

gen after_x_dist_30_40 = after*dist_30_40

gen after_x_dist_40_50 = after*dist_40_50

reg log_transaction_price log_real_surface rooms_nr i.year i.zip_code i.function_code
log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users
log_car_users log_dist_metro after_x_dist_0_10 after_x_dist_10_20 after_x_dist_20_30
after_x_dist_30_40 after_x_dist_40_50, robust
```

Regression Model 3: Base model REV only

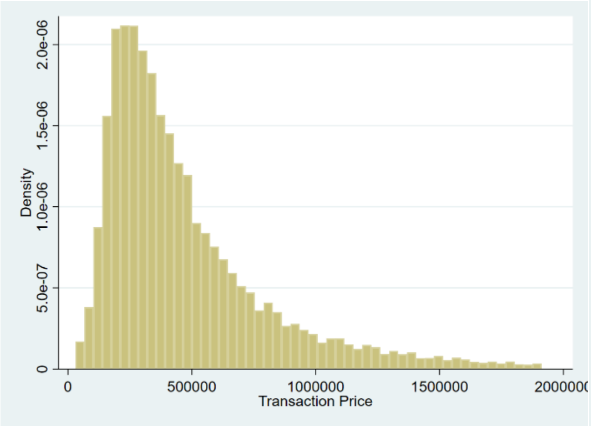
```
drop if location =="Rue LeCourbe"

drop if location =="Avenue de Flandre"

drop if location == "Boulevard de Arago"

reg log_transaction_price i.year i.zip_code i.function_code after target_50m after_x_target50m, robust
```

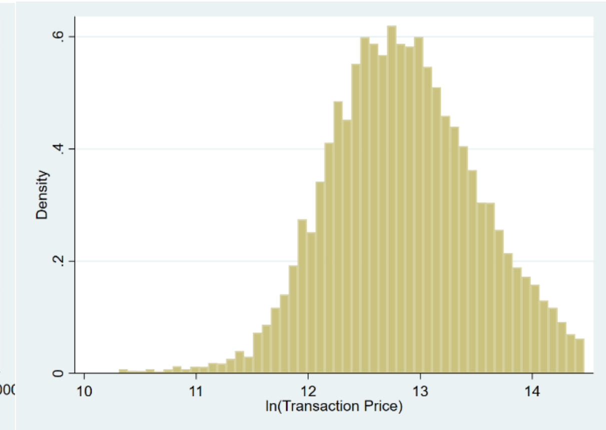
Regression Model 4: Base model REV only + control variables

```
reg log_transaction_price log_real_surface rooms_nr i.year i.zip_code i.function_code
log_unemployment_pct log_education_pct log_immigrants_pct log_singles_pct log_bike_users
log_car_users log_dist_metro after target_50m after_x_target50m, robust
```

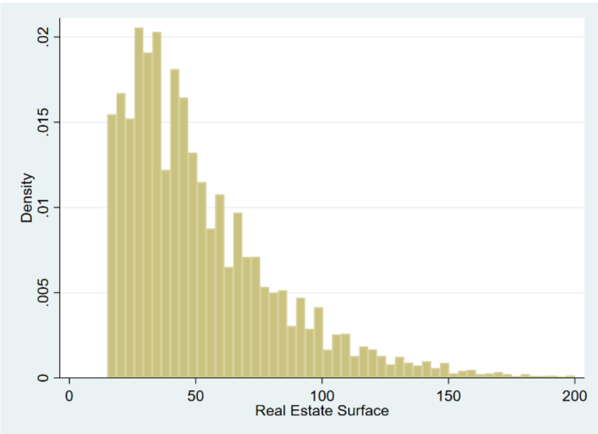
APPENDIX C | HISTOGRAMS

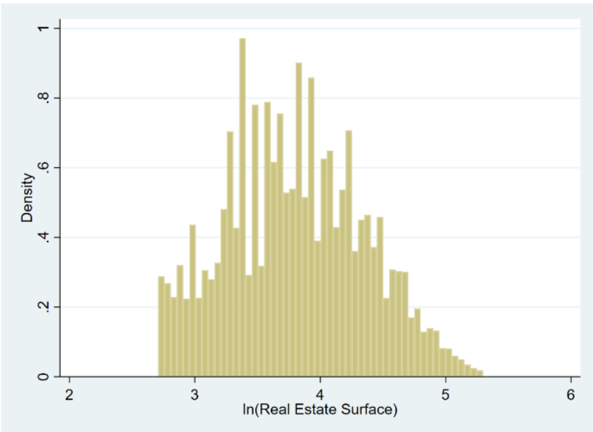
Histogram C.1 & C.2.: Transaction Price and ln(transaction price)



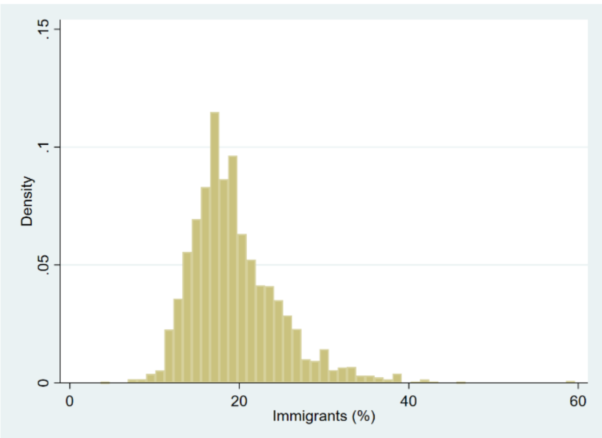


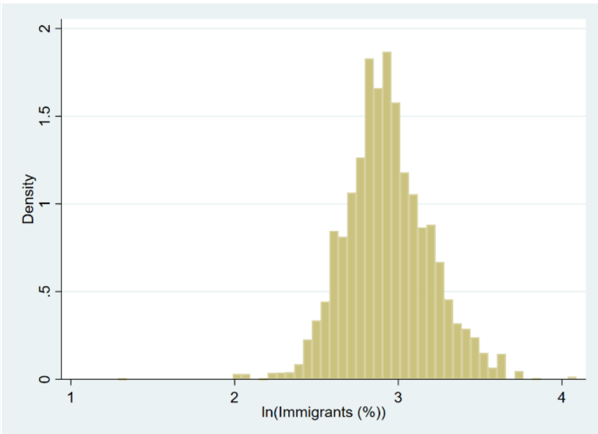
Histogram C.3 and C.4: Real Estate Surface and ln(Real Estate Surface)



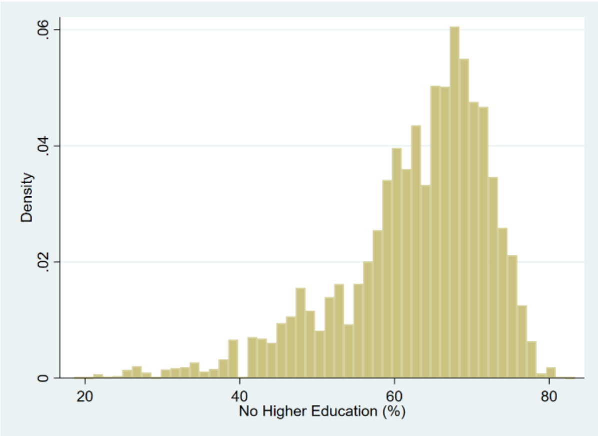


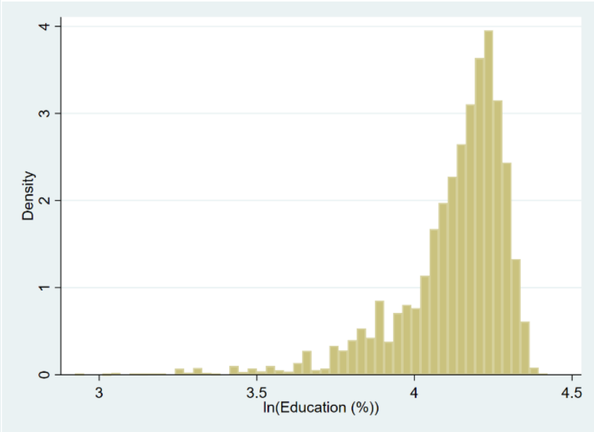
Histogram C.5 and C.6: Immigrants (%) and ln(Immigrants)



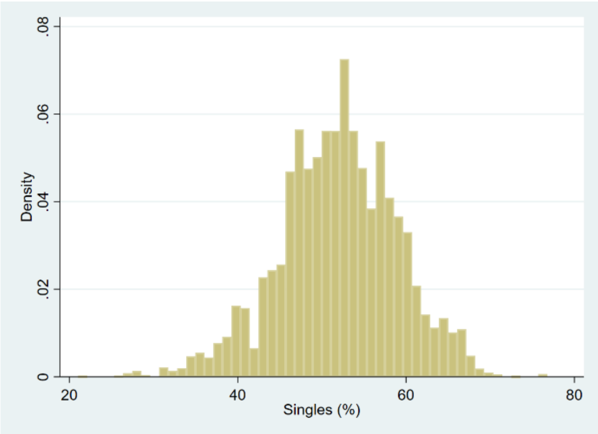


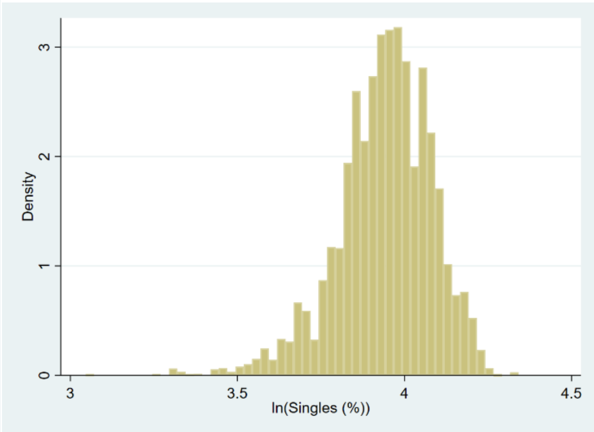
Histogram C.7 and C.8: No Higher Education (%) and ln(No Higher Education)



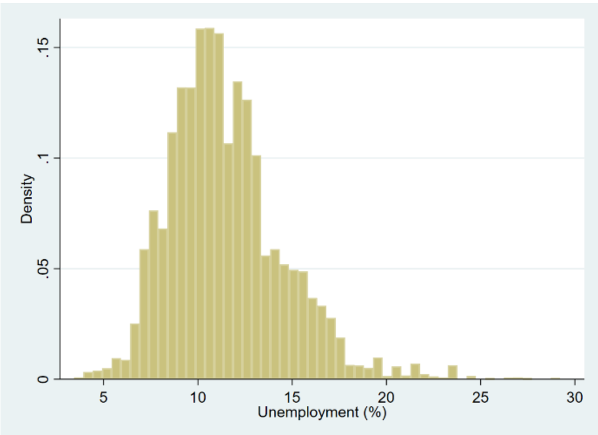


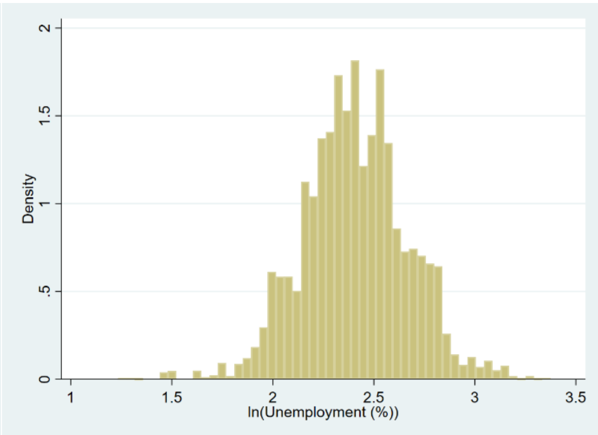
Histogram C.9 and C.10: Singles (%) and ln(Singles)



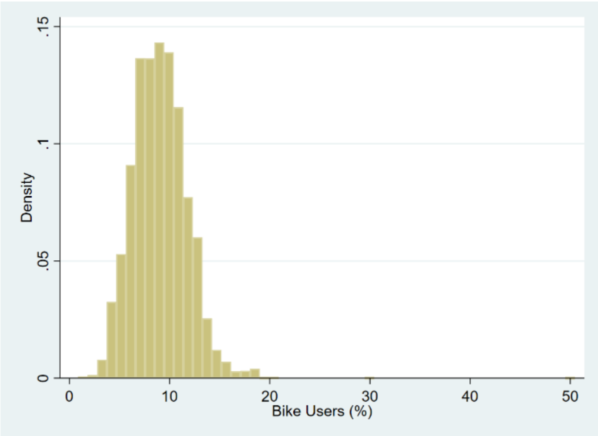


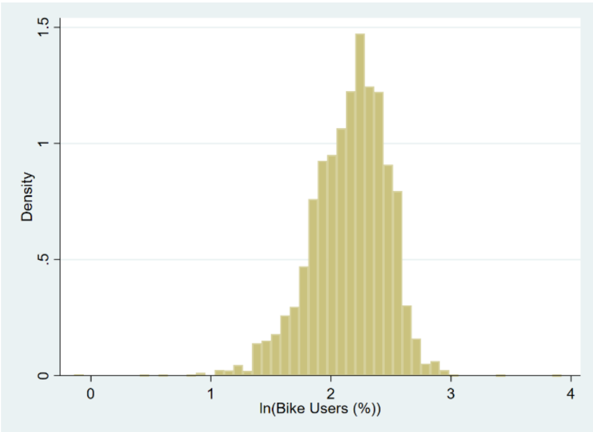
Histogram C.11 and C.12: Unemployment (%) and ln(Unemployment)



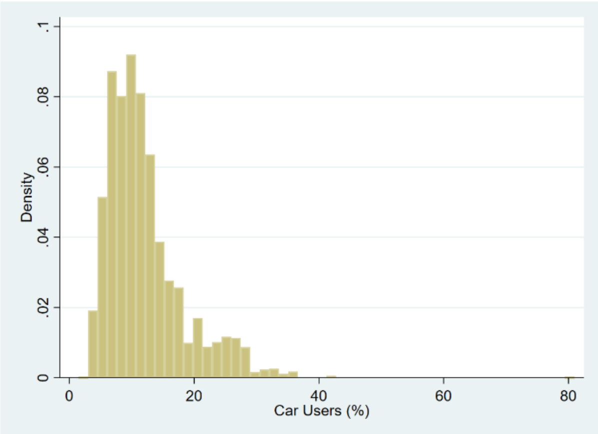


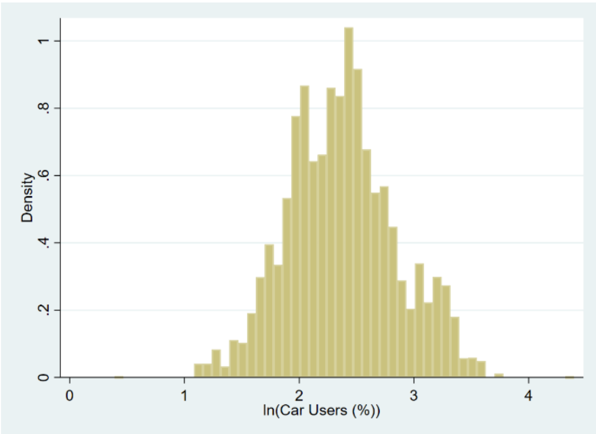
Histogram C.13 and C.14: Bike Users (%) and ln(Bike Users)



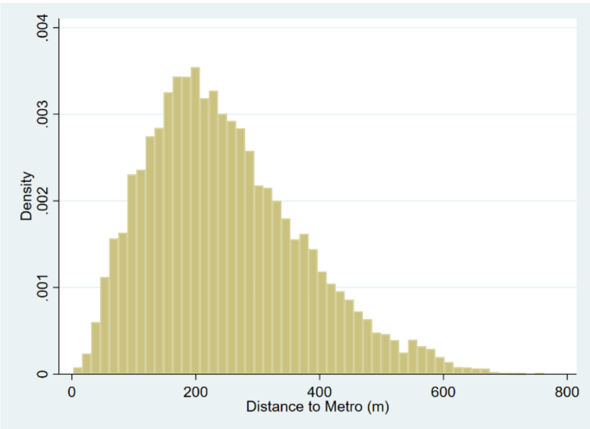


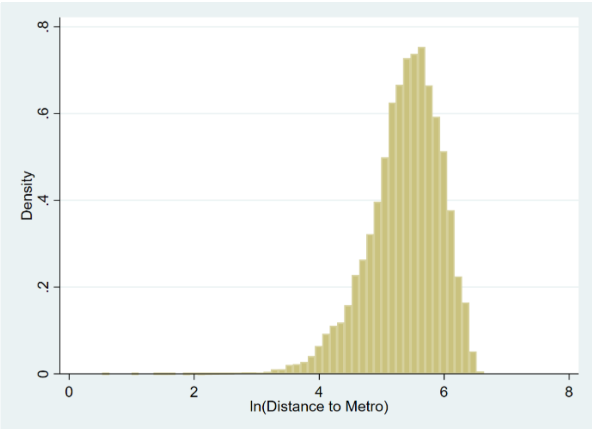
Histogram C.15 and C.16: Car Users (%) and ln(Car Users)



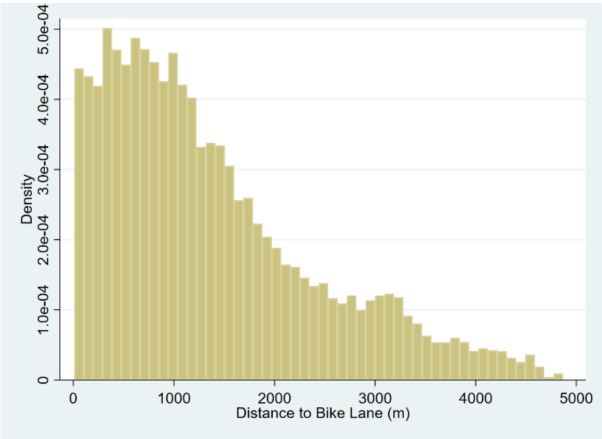


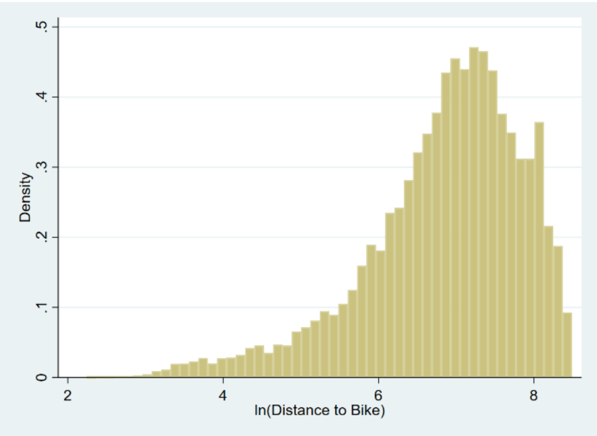
Histogram C.17 and C.18: Distance to Metro & ln(Distance to Metro)



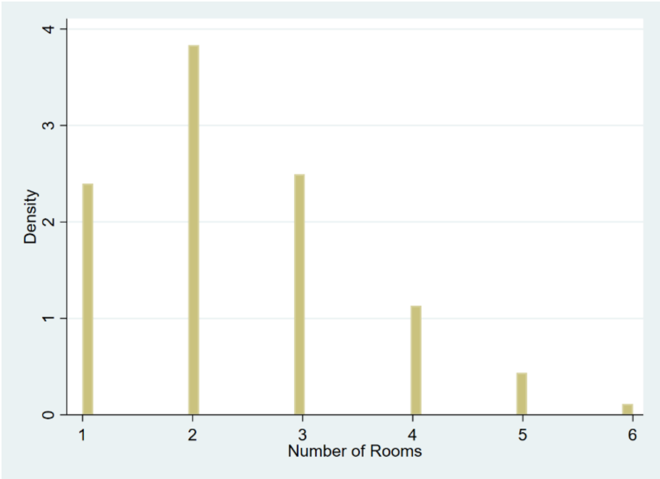


Histogram C.19 and C.20: Distance to Bike Lane & ln(Distance to Bike Lane)





Histogram C.21: Number of Rooms



APPENDIX D | OLS ASSUMPTIONS TESTING

There are five assumptions that need to be tested in order to be sure that the coefficient estimates from the regressions and the associated standard errors are valid. If these five assumptions are met, the method can be seen as being BLUE: Best Linear Unbiased Estimator (Brooks and Tsolacos, 2010), which means an unbiased prediction of the coefficients. The five assumptions that should be met are as follows:

Table D.1: OLS assumptions. Source: Brooks & Tsolacos (2010).

Assumption	**Formula**	**Description**
1: Linearity	$E(u_t) = 0$	The average value of the errors is zero
2: Homoscedasticity	$var(u_t) = \sigma^2 < \infty$	The variance of the errors is constant and finite
3: No autocorrelation	$cov(u_i, u_j) = 0 \; for \; i \neq j$	The covariance between the error terms is zero, which means no autocorrelation
4: Independence	$cov(u_t, x_t) = 0$	The regressors are non-stochastic, they are not related to the error terms
5: Normality of errors	$u_t \sim N(0, \sigma^2)$	The error terms are normally distributed

Testing assumption 1: linearity

A histogram of the residuals is made and shown in **figure D.1.** A somewhat normal distribution of the residuals can be identified, with the mean of the errors being approximately zero. Besides, the first assumption will never be violated whenever there is a constant (α) included in the regression (Brooks and Tsolacos, 2010). STATA automatically includes a constant term in the regressions. This first assumption will thus not be violated in the regression.

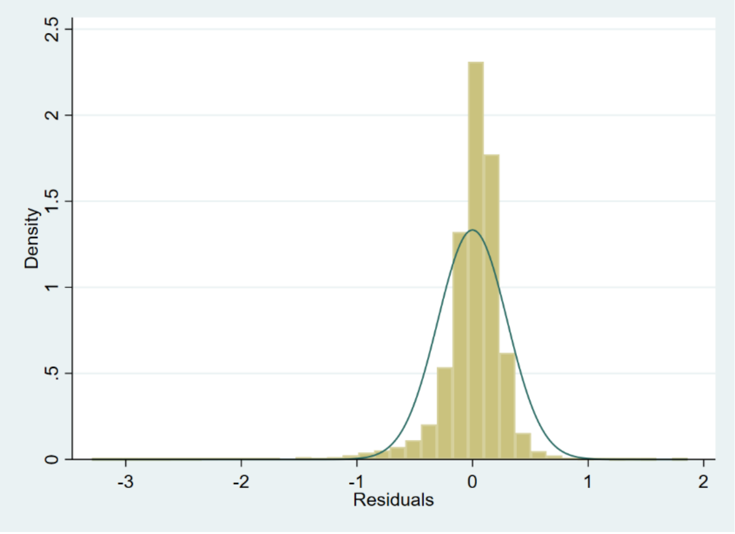


Figure D.1: Histogram of the residuals

Testing assumption 2: homoskedasticity

There are two ways to test for homoskedasticity. There is a visual test, the RVF-test, which can be seen in **figure D.2.** In this figure, a clear pattern in the data can be seen, indicating heteroskedasticity. Furthermore, the Breusch-Pagan/Cook-Weisberg statistical test is used to test whether there really is the issue of heteroskedasticity in the data. The null hypothesis of this test is that there is a constant variance, thus no heteroskedasticity. According to the test results, which can be found in **table D.2**, the null hypothesis needs to be rejected. This means that there is indeed heteroskedasticity in the data. This issue can be solved by including clustered standard errors in the regression.

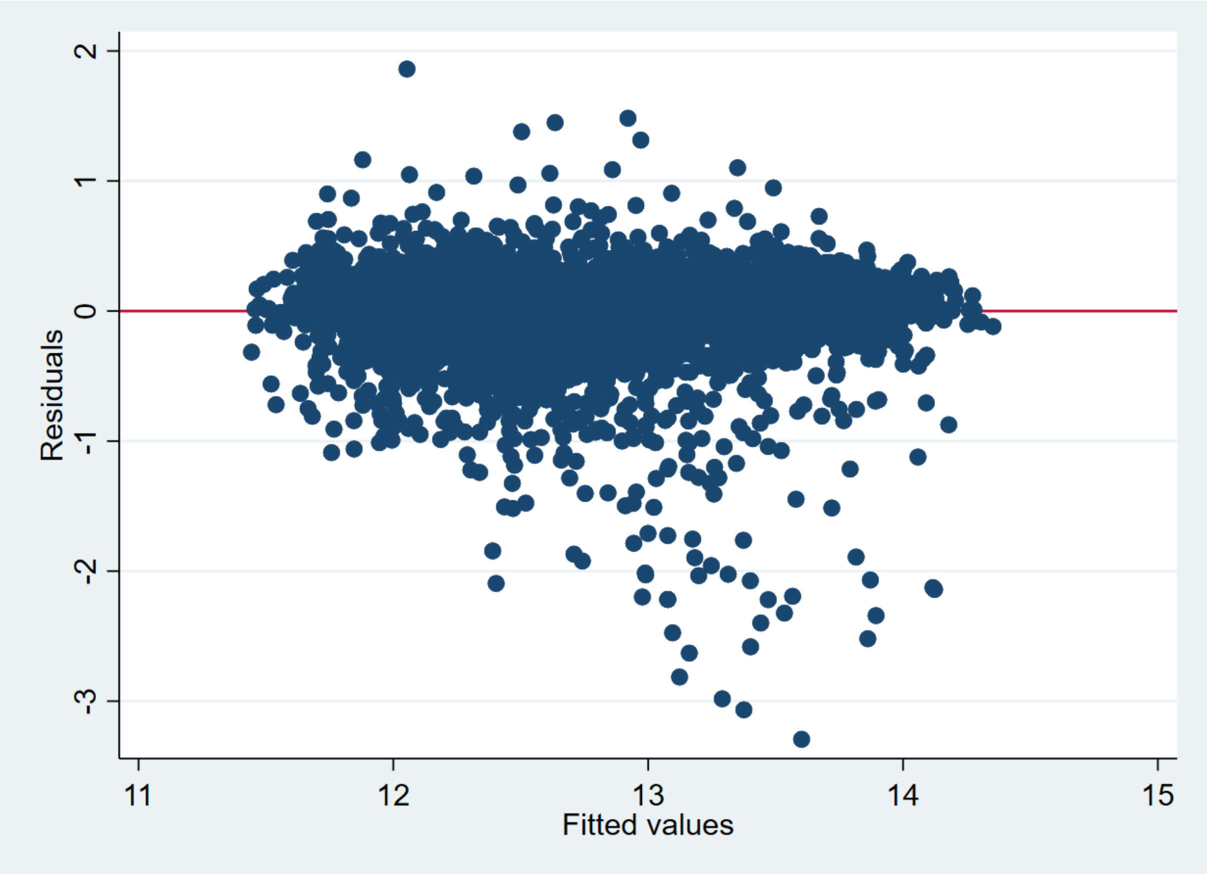


Figure D.2: RVF Test

Table D.2: Breusch Pagan/Cook-Weisberg test for heteroskedasticity.

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity	
H0	Constant variable
Variables	Fitted values of log_transaction price
Chi2(1)	98.52
Prob > chi2	0.0000

Testing assumption 3: no autocorrelation

According to assumption 3, the error terms should be uncorrelated with each other. According to the correlation matrix in **table D.3,** some autocorrelation can be found in the data (indicated with an asterisk in the table). This assumption is thus violated as well, although some extend of autocorrelation can be found in almost every regression in real estate (Brooks and Tsolacos, 2010). Firstly, since all variables are well below 10 in the VIF-analysis in **table D.4**, no variables are removed from the regression. Furthermore, this issue can be easily solved by including clustered standard errors in the regression.

Testing assumption 4: Relation between error terms and regressor

Assumption four validates whether the regressors are non-stochastic, which means that they are not related to the error terms. By calculating the residuals of the variable "Distance to Bike Lane" on the dependent variable ln(Transaction Price), it has been found that the residuals do not have a significant effect. This means that this regressors are not stochastic.

Testing assumption 5: Normality of the error terms

Lastly, it is checked whether the error terms are normally distributed. This is shown in a Kernel Density Plot, as seen in **figure D.3.** Also, a normal probability plot (pnorm) is shown in **figure D.4.** It seems that the error terms do not perfectly follow the normal lines, which indicates that the error terms are not perfectly normal. However, Brooks and Tsolaco (2010) state the following about normality of the error term:

"for sample sizes that are sufficiently large, violation of the normality assumption is virtually inconsequential (…) in economic and real estate modelling, it is quite often the case that one or two extreme residuals cause a rejection of the normality assumption. Such observations would appear in the tails of the distribution (…) which enters into the definition of kurtosis, to be very large" (Brooks and Tsolaco (2010), pp. 168-169).

Since this research is of sufficiently large size, a possible violation of this assumption is seen as being without consequences. However, to help the normality, most variables in this research have been transformed into a natural logarithm (ln).

Table D.3: Matrix of correlations of the variables in this research.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) log_transaction_price	1.000															
(2) log_real_surface	0.847*	1.000														
(3) rooms_nr	0.713*	0.829*	1.000													
(4) zip_code	-0.120	-0.015	0.017	1.000												
(5) year	0.107	-0.010	-0.019	0.012	1.000											
(6) log_unemployment	-0.159	-0.118	-0.087	-0.127	0.008	1.000										
(7) log_education	0.233	0.113	0.103	-0.295	-0.019	-0.637*	1.000									
(8) log_immigrants	-0.161	-0.077	-0.078	-0.018	0.045	0.701*	-0.699*	1.000								
(9) log_singles	0.038	-0.049	-0.026	-0.476	-0.024	0.052	0.297	-0.135	1.000							
(10) log_bike_users	0.081	0.038	0.083	-0.152	-0.009	-0.029	0.306	-0.162	0.078	1.000						
(11) log_car_users	0.001	0.036	0.028	0.729*	0.001	-0.322	0.002	-0.312	-0.345	-0.318	1.000					
(12) log_dist_metro	0.010	-0.012	-0.042	0.241	0.014	-0.241	0.230	-0.182	-0.052	-0.206	0.401	1.000				
(13) log_dist_bike	-0.073	-0.062	-0.101	-0.080	0.008	0.002	-0.015	0.063	-0.026	-0.019	-0.100	-0.011	1.000			
(14) after	0.110	0.007	0.004	0.022	0.774*	-0.000	-0.005	-0.030	-0.005	0.021	0.015	-0.005	0.004	1.000		
(15) target_50m	0.045	0.041	0.077	0.069	-0.005	0.046	-0.029	-0.026	0.053	-0.001	0.072	0.010	-0.855*	-0.004	1.000	
(16) after_x_target_50m	0.080	0.019	0.041	0.043	0.430	0.031	-0.016	-0.016	0.043	0.011	0.032	-0.004	-0.403	0.558*	0.480	1.000

NOTE: Correlations between variables are shown in the table. High correlations (>0.5) are indicated with an asterisks (*).

Table D.4: VIF analysis of the variables of this research.

	VIF	1/VIF
Log_real_surface	3.330	0.301
Rooms_nr	3.340	0.299
Year		
2015	1.850	0.542
2016	1.850	0.541
2017	2.140	0.467
2018	3.930	0.255
2019	4.110	0.243
Zip Code		
75002	3.340	0.299
75003	3.160	0.317
75004	2.160	0.462
75005	1.570	0.638
75010	7.820	0.128
75011	15.120	0.066
75013	7.970	0.125
75014	5.190	0.193
75015	24.840	0.040
75019	11.550	0.087

	VIF	1/VIF
Log_real_surface	3.330	0.301
Log_unemployment	3.540	0.282
Log_education	6.000	0.167
Log_immigrants	4.700	0.213
Log_singles	2.590	0.386
Log_bike_users	1.980	0.506
Log_car_users	7.800	0.128
Log_distance_metro	1.480	0.677
After	5.110	0.196
Target_50m	1.580	0.634
After_x_target_50m	2.210	0.453
Mean VIF	**5.040**	

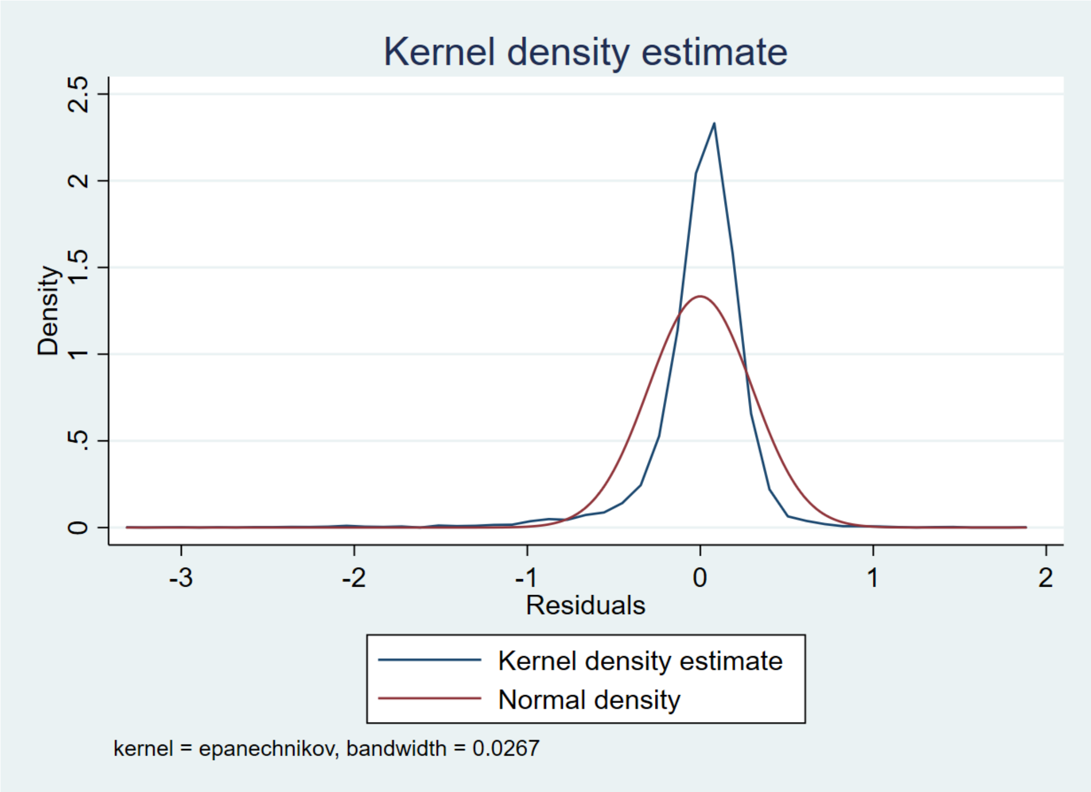


Figure D.4: Kernel Density Plot

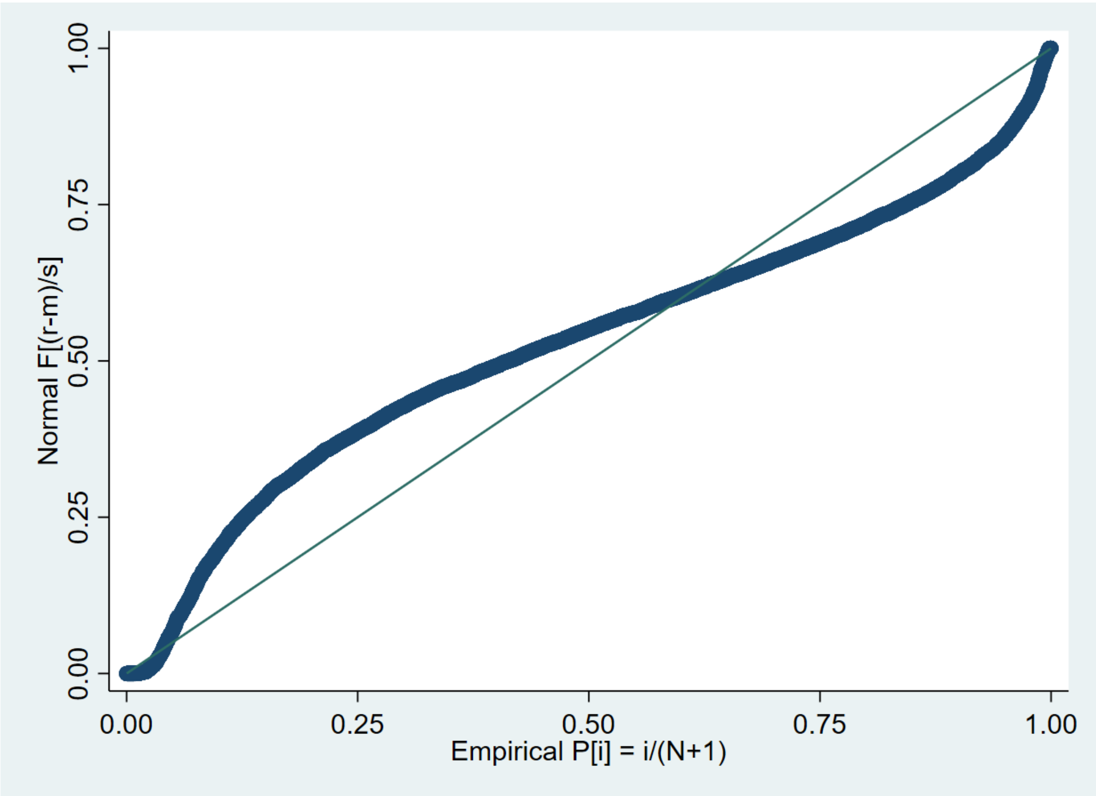


Figure D.5: Normal Probability Plot (pnorm)

APPENDIX E | FULL REGRESSION OUTCOME

Regression Model 1

	Full Sample		REV Only	
	(1)	(2)	(3)	(4)
VARIABLES	ln(Transaction Price)	ln(Transaction Price)	ln(Transaction Price)	ln(Transaction Price)
ln(Real Estate Surface)		0.931***		0.951***
		(0.0133)		(0.0181)
Number of Rooms		0.0226***		0.0125
		(0.00641)		(0.00926)
Year = 2015	-0.0164	-0.0159	-0.0183	-0.0222
	(0.0254)	(0.0123)	(0.0348)	(0.0176)
Year = 2016	-0.0192	0.00463	-0.0377	-0.0109
	(0.0256)	(0.0127)	(0.0349)	(0.0173)
Year = 2017	0.0664**	0.0816***	0.0629*	0.0862***
	(0.0265)	(0.0130)	(0.0374)	(0.0187)
Year = 2018	0.119***	0.156***	0.185***	0.185***
	(0.0393)	(0.0185)	(0.0538)	(0.0253)
Year = 2019	0.135***	0.204***	0.179***	0.219***
	(0.0436)	(0.0213)	(0.0613)	(0.0306)
Zip Code = 75002	-0.0941	-0.0531	-0.0892	-0.0833*
	(0.0583)	(0.0367)	(0.0581)	(0.0428)
Zip Code = 75003	0.0723	0.0247	0.0761	-0.0545
	(0.0591)	(0.0393)	(0.0590)	(0.0498)
Zip Code = 75004	0.160**	0.0950**	0.160**	0.0620
	(0.0670)	(0.0371)	(0.0666)	(0.0465)
Zip Code = 75005	-0.0263	-0.0443		
	(0.107)	(0.0594)		
Zip Code = 75010	-0.111**	-0.144***	-0.0915*	-0.207***
	(0.0496)	(0.0380)	(0.0497)	(0.0520)
Zip Code = 75011	-0.139***	-0.114***	-0.133***	-0.161***
	(0.0459)	(0.0341)	(0.0458)	(0.0446)
Zip Code = 75013	-0.117**	-0.0763*		
	(0.0533)	(0.0410)		
Zip Code = 75014	0.319***	-0.0500		
	(0.0599)	(0.0505)		
Zip Code = 75015	-0.0625	-0.0798*		
	(0.0457)	(0.0426)		
Zip Code = 75019	-0.497***	-0.277***		
	(0.0483)	(0.0450)		
Function Code = 2	-0.474*	-0.146		
	(0.276)	(0.160)		
ln(Unemployment (%))		0.0605**		-0.00622
		(0.0239)		(0.0443)
ln(Education (%))		0.239***		-0.132
		(0.0569)		(0.123)
ln(Immigrants (%))		-0.0751**		0.0134
		(0.0295)		(0.0506)
ln(Singles (%))		0.00798		-0.0538
		(0.0512)		(0.111)
ln(Bike Users (%))		0.0431**		0.0956***
		(0.0196)		(0.0318)
ln(Car Users (%))		-0.0138		0.0254
		(0.0207)		(0.0354)
ln(Distance to Metro)		-0.00261		0.00785
		(0.00735)		(0.0105)
After	0.0364	-0.00681	0.00873	-0.0128
	(0.0353)	(0.0173)	(0.0490)	(0.0238)
Target (50m)	0.0757***	0.0140	0.117***	0.00115
	(0.0182)	(0.00919)	(0.0260)	(0.0134)
After * Target(50m)	0.000361	0.00340	-0.0263	0.0112
	(0.0313)	(0.0159)	(0.0443)	(0.0220)
Constant	13.31***	8.421***	12.82***	9.714***
	(0.280)	(0.346)	(0.0511)	(0.824)
Observations	6,741	6,741	3,594	3,594
R-squared	0.080	0.763	0.042	0.750

NOTE: The dependent variable is ln(Transaction Price). Robust standard errors can be found in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Regression Model 2: Alternative Specification

VARIABLES	(5) ln(Transaction Price)
log_real_surface	0.930***
	(0.0134)
rooms_nr	0.0231***
	(0.00642)
2015.year	-0.0153
	(0.0123)
2016.year	0.00459
	(0.0127)
2017.year	0.0792***
	(0.0126)
2018.year	0.146***
	(0.0136)
2019.year	0.194***
	(0.0150)
75002.zip_code	-0.0546
	(0.0368)
75003.zip_code	0.0237
	(0.0395)
75004.zip_code	0.0960**
	(0.0374)
75005.zip_code	-0.0512
	(0.0594)
75010.zip_code	-0.145***
	(0.0383)
75011.zip_code	-0.117***
	(0.0343)
75013.zip_code	-0.0793*
	(0.0412)
75014.zip_code	-0.0583
	(0.0506)
75015.zip_code	-0.0798*
	(0.0429)
75019.zip_code	-0.278***
	(0.0453)
2.function_code	-0.142
	(0.159)
log_unemployment_pct	0.0621***
	(0.0238)
log_education_pct	0.234***
	(0.0568)
log_immigrants_pct	-0.0788***
	(0.0293)
log_singles_pct	0.0128
	(0.0515)
log_bike_users	0.0448**
	(0.0196)
log_car_users	-0.0132
	(0.0208)
log_dist_metro	-0.00273
	(0.00734)
o.after_x_dist_0_10	-
after_x_dist_10_20	0.0443
	(0.0295)
after_x_dist_20_30	0.0317
	(0.0151)
after_x_dist_30_40	-0.00294
	(0.0213)
after_x_dist_40_50	0.0134
	(0.0197)
Constant	8.429***
	(0.345)
Observations	6,741
R-squared	0.763

NOTE: The dependent variable is ln(Transaction Price). Robust standard errors can be found in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$