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BI Norwegian Business School

Master Thesis

Housing Price Analysis on Station Proximity and the Development of New Commuter Rails in the Suburbs of Oslo

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Abstract

This thesis investigates the relationship between station proximity and housing prices and the effect of developing new commuter rails. We consider a log-linear hedonic pricing model utilizing almost 20 years of property transactions from the suburban cities Ski and Lillestrøm. We establish the relationship between housing prices and station proximity for both cities, generating housing price discounts of 14.87% and 8.91% for every kilometer the distance increases. Further, this relationship is linear for Ski, while Lillestrøm received the largest premium for the area between 250 to 500 meters away from the station, resulting in a non-linear relationship. For the development of new commuter rails, our results showed a decreasing price trend in Ski. However, Lillestrøm gave few significant results, making a conclusion hard to draw.

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1. Introduction

The Norwegian housing market has been a widely discussed topic for many years. Prices have been steadily rising, and there are many speculations on the driving forces of the growth. The location of a property has, for many, become one of the most important attributes of a home. People desire to live where it is easy to commute to their work, schools, and other daily used facilities, and the quality of public transportation is therefore important for many home buyers. Throughout the years, station proximity's effect on housing prices has been researched in several parts of the world. Studies show positive and negative effects of living close to a commuter station, but the different results vary according to where the study was conducted. For our thesis, we have decided to investigate the housing price effects of proximity to commuter stations in two suburbs of Oslo, Lillestrøm and Ski. This thesis aims to address the following research question together with the two sub-questions:

Does proximity to commuter railway stations yield a housing price premium?

- *Is there a linear relationship between an increase in housing price discounts and a decrease in station proximity?*
- *Can we observe a positive capitalization in housing prices by the development of new commuter rails?*

The increasing desire to reside in a central location has significantly pushed up real estate prices throughout the years. Returning to basics, supply- and demand theory portrays housing prices in the following manner: as a location site becomes more appealing due to particular attributes, demand rises, and the bidding procedure drives prices higher. Near business districts, specific traits or activities in mind can be discovered. As a result, proximity to the city center is a desirable feature that drives up housing prices. This is the known trend in Oslo. For years, the price gain has reached new monthly records, and according to Eiendom Norge, the prices in Oslo have increased by 99.9% over the last decade (Lauridsen, 2021). Investment in transportation infrastructure, such as commuter railways, has been used as a tool to spread the population (Fejarang, 1994).

A thorough study by Bhatta and Drennan from 2003 summarizes earlier research articles on investment in public transportation and evaluates the positive effects. The study implies that long-term economic benefits have resulted from such investment (Bhatta & Drennan, 2003). The same investment in public transportation has been done, and is being done, around Oslo. Developing high-speed train rails makes commuting to Oslo efficient and easy (Bane NOR, 2021b). Recent trends have shown increased relocation patterns to the suburbs around the capital, implying higher demand for housing in the suburbs (Høydahl, 2022). This will, to some extent, lower demand in and around city centers by attracting residents to relocate outside of the city but near commuter stations (Fejarang, 1994).

In this thesis, we assess two time periods of almost 20 years of property transactions in a period with commuter rails development in Ski and Lillestrøm. By applying a theoretically well-established hedonic pricing methodology (Rosen, 1974), we compare the suburb cities for proximity effects, and changes before and after the development of commuter rails. To our knowledge, such exact research has not been performed in cities close to Oslo, and we hope our research will be a valuable contribution to existing research.

We quickly decided on the housing market when choosing the topic for our master thesis. We find the evolution of the housing market especially interesting as housing investments have given very high returns in the past decades, and housing prices have been rising yearly. The market has not seen a long-lasting decline since the late 80s, and since that, the Norwegian economy has been experiencing a rise. Especially the big cities have seen a high property price increase. As our lives are based in and around Oslo, and we are entering the housing market, we find the topic of Oslo's suburbs highly relevant, also on a personal level. Therefore, we decided on station proximity effects as our master thesis.

2. Literature Review

2.1 Hedonic Pricing Theory

Hedonic pricing methodology, introduced by Rosen in 1974, made it easier for researchers to estimate the value each attribute had on housing prices. In practical economic research, hedonic price analysis is a prominent tool. The technique has been used to capture the marginal contribution of several features to the total sales price of various tangible assets, particularly housing (Lancaster, 1966; Rosen, 1974). As a result, we observe models attempting to explain variation in property values, incorporating extrinsic and intrinsic attributes of properties.

Various intrinsic and extrinsic features have been considered for analysis of the housing market when conducting previous research. Our thesis will emphasize the proximity to rail stations as an essential extrinsic factor when valuing properties. Earlier empirical studies on this area amplify the importance of accessibility as a benefit of proximity to stations. Even though the studies vary in methodology and research area, the majority have used hedonic pricing as the preferred methodology.

2.2 Previous Research – Review

The outcomes of the encountered empiric have shown contradictory results on station proximity and housing price impact. Dubé et al. (2013), Al-Mosaind et al. (1993), Ferguson (1984), and Voith (1991) are some studies that all conclude with price premiums for properties closer to the stations compared to properties further away. Dubé et al.'s (2013) study focus on developing new commuter rails and how this affects value. This study emphasizes the price premium that comes from the increased accessibility houses experience by the proximity to new stations. The study also underscores the economic effect of increased property tax from increased housing value due to commuter rail investments. Al-Mosaind et al. (1993) also mention that proximity to commuter rails will reduce commuter costs and that the reduction will be positively capitalized in the housing value.

Ferguson (1984) investigated price premiums related to improvements in transportation. He specifically looked at pre-service effects as his study was done during the construction of a new rapid transit system in Vancouver. This study showed that the construction led to a price premium 2.5 years prior to operation of the new transit system, and they could not find any negative externalities. Voith (1991) looks at accessibility to employment and transportation systems and how this affects housing values, where people choose to live, and whether or not people own a car. The study finds that the suburban areas with the best commuter rail connection to the central business districts have a house value premium of 6.4% compared to similar neighborhoods and that the suburbs house most of the labor force.

Other studies did not find proof that supports the evidence from the already mentioned studies. Duncan (2011), Landis et al. (1994), and Gatzlaff & Smith (1993) all conducted studies that found small or no significant impact on increased property values when being closer to railway stations. Landis et al. (1994) found the need for several explanatory factors besides station proximity to justify the value impact. Gatzlaff & Smith (1993) did a double study to see if they could find any significant price impact of station proximity. First, they compared a resale house price index for the houses close to the station to a regular house price index. Then they conducted a hedonic regression. None of their models indicated strong evidence of property price premium from station proximity. They suggest a reason for the lack of impact could be the already existing accessibility connected to proximity to highways.

In Duncan's (2011) study from San Diego, they focused on developing sustainable transport systems that are less auto-dependent. Their model showed that proximity to a station had a significantly stronger effect on housing prices when the station was located in a pedestrian-oriented environment, meaning that the station was easily accessible without car transportation. In Norway, we see a trend of cities forming around stations, resulting in the stations being within walking distance from people's homes. This makes the stations more valuable to the public as the train can be seen as the preferred and easiest form of transport. These cities are called station cities (Wisting, 2021). In these cities, the stations are located in the city center, and the areas around the stations are usually well-developed urban communities. We have chosen to do our analysis on two Norwegian station cities with high-speed commuter rails to Oslo. The cities have well-developed city centers that fulfill the criteria of a pedestrian-oriented environment mentioned in Duncan's (2011) study.

Another characteristic of the station cities is that they are usually not large cities. Some of the quality of the city is in fact the station itself. Chen & Haynes (2015) found that the effect of station proximity is only noticeable in small and medium cities. It is natural to assume that this is because the commuter rails are mostly valuable for residents of the suburbs as they are the main users. They use the commuter rails to travel to and from the big cities or central business districts for work, school, or other activities. Hence, the property effect is higher in the smaller, suburban cities.

Other studies found negative effects of proximity to stations. Armstrong & Rodriguez (2006) concluded that station proximity had a negative impact on housing prices due to the noise and crime effects. Bowes and Ihlanfeldt (2001) also wanted to investigate negative externalities of increased noise pollution, unsightliness of the station, and crime that may come with station proximity. Their hedonic model gave them mixed results. It showed that houses within a quarter mile from the station were sold at a discount of 19% compared to the houses more than three miles from the station. However, the model also showed that the properties located between these distances experienced the greatest premium from station proximity. A study in Oslo by Strand & Vågnes (2001) studied the effect proximity to the railroad had on housing prices. Their study showed that properties within a 100-meter radius from the railroad were the only ones affected, and they found a negative price effect for these properties.

The method of proximity measurement has been examined in various research, and it is a fundamental methodological theme when calculating the effect of proximity on property values. In general, there are two main categories of empiric analysis on proximity; a continuous measure of distance from the train station to properties and distance category ring bands measured as dummies, with properties falling within or outside the ring bands. Some studies have been forced to choose between the two methods due to inadequate data sets, restrictions, or preferences (Bowes & Ihlanfeldt, 2001; Duncan, 2011). Other studies have merged the two approaches in their analysis (Al-Mosaind et al., 1993; Dubé et al., 2013). By combining both and utilizing the data available, the analysis may appear more thorough and explaining.

When it comes to settling down in a new location, accessibility can be a crucial consideration. As a result, a high-quality commuter rail system may provide commuters and families with easy access to their workplaces, schools, and other activities. In general, empirical research on the effects of transportation on real estate has found that greater accessibility is associated with higher property values. However, as research has shown, proximity to railway stations can have neutral and negative effects, making this topic relevant for further research.

3. Study Area

3.1 Selection Criteria

We had some criteria in mind when deciding on the area for our investigation.

- First, we wanted to look for commuter regions in the vicinity of Oslo, our nearest big city.
- Second, the areas needed to have a commuter rail system in place or being under construction.
- Third, locations where we could access data. We also wished for several areas to conduct our analysis on, as this would support our research.

We chose Lillestrøm early on as this is one of the largest commuter areas close to Oslo, and the property values have been increasing over the years. To make our analysis more robust and comparable, we decided to choose Ski as the other city to investigate.

Lillestrøm and Ski are located with respectively 10- and 11-minute travel from Oslo Central Station by the cities' newest commuter railways. For Ski, the train ride has for a long time been twice the length with 22 minutes, but when the new Follobanen opens by the end of 2022, the time will be halved (Bane NOR, 2021a). The difference between the two cities is that Lillestrøm got its commuter railway in 1999 in connection with the opening of Oslo's new airport at Gardermoen. Ski will, as mentioned, get its new commuter railway by the end of this year, 2022. The railways make both cities desirable places to live for people working in Oslo. Additionally, as housing prices have doubled in Oslo over the past ten years, people have started looking elsewhere for more affordable places to live, still retaining a short commute to the center of Oslo.

3.2 Description of Study Area

3.2.1 Lillestrøm

Lillestrøm is both the name of a city and a municipality. In our thesis, we will focus on Lillestrøm, the city. It is located in Romerike district and works as the region's center. The city holds the local district court and police department, as well as the town hall of the municipality of Lillestrøm. Lillestrøm is also classified as a suburb of Oslo, and the city has approximately 18.500 citizens (Thorsnæs & Askheim, 2021).

Over the years, Lillestrøm has seen extensive development with new restaurants, a shopping mall, nightlife, and increased cultural activities, making the city less dependent on Oslo's offers. The city has a variety of apartment complexes, single-family housing, and townhouses. There has also been a massive increase in housing development, and there are currently several large ongoing housing projects, creating rapid population growth for the years to come.

3.2.2 Ski

Ski is a city located in Nordre Follo and Ås municipalities in Viken county with approximately 20.500 citizens. The city is situated southeast of Oslo. Similar to Lillestrøm, Ski holds the local district court and police department. There is also a local hospital located close to the city center in Ski.

Ski has many facilities like restaurants, a large shopping mall, and different cultural offers, but it is less developed than Lillestrøm. Ski is still under development, and the city will grow rapidly in the upcoming years. There are several large ongoing development projects in the city. There are plans to build and develop 70,000 square meters of housing, stores, and urban space in the following years, making Ski an even more attractive place for people to live and work as a suburb of Oslo (Widing, 2018).

3.3 Commuter Rails

3.3.1 Romeriksporten

Romeriksporten has for many years been Norway's longest railway tunnel, of 14.6 kilometers, and was put into operation on August 22nd, 1999 ("Romeriksporten," 2020). The tunnel is located between Stalsberg in Lillestrøm and Etterstad in Oslo and is a part of Gardemobanen, which opened in 1998 ("Romeriksporten," 2020). The new tunnel reduced the commute from Lillestrøm to Oslo from around 30 to 10 minutes.

3.3.2 Follobanen

Follobanen is the newest railway project in Norway. It is a double-track, high-speed railway from Oslo to Ski, increasing the train capacity along the South Corridor. The project is set to be completed by December 2022, and the Blix tunnel will take over the record as the longest railway tunnel in the Nordic countries, with its 22 kilometers (BaneNOR, 2021).

4. Methodology

4.1 Hypotheses

We have made three hypotheses to validate the investigation of our research questions. These are based on what we believe we will find from our analysis results and are presented below:

1. Station proximity capitalizes a premium on housing prices.

The first hypothesis is made to establish whether properties capitalize on being located close to a train station. We believe there is a premium on station proximity.

2. Decreasing station proximity is steadily increasing housing price discounts.

The second hypothesis is included as an extension of our first hypothesis. We believe there is a linear relationship between station proximity and housing prices.

3. Development of new commuter rails increases prices of existing houses.

Lastly, the third hypothesis addresses whether we can detect an increase in housing prices by developing new commuter rails. As such a development will strengthen the accessibility and lower commuting expenses, we believe it will unfold itself as a positive capitalization on housing prices.

4.2 Hedonic Pricing Model

The hedonic pricing model is a widely used econometric technique for analyzing real estate prices and the factors that impact them. The hedonic model considers real assets to be made up of various traits that characterize their utility to the person who consumes them (Brooks, 2019). The theory behind hedonic pricing has been well established by Rosen (1974). However, it has been unclear which model to employ in hedonic pricing research. A study by Halvorsen and Pollakowski (1981) found it challenging to suit a functional form to hedonic price functions, underpinned by economic theory. They recommended using Box-Cox transformation for hedonic analysis (Halvorsen & Pollakowski, 1981). The same approach was used by Linneman (1980) and Blomquist and Worley (1981) in a hedonic analysis of the housing market.

However, more recent research has found that this approach has several drawbacks. Cassel and Mendelsohn (1985) published a comment on Halvorsen and Pollakowski's study from 1981. They criticized the Box-Cox methodology for being functional at the expense of other essential criteria. Lack of coefficient accuracy, imprecise variable prediction results, and overly complex slope estimations made the results too challenging to work with. Smith and Gihring (2006) reviewed and summarized more than 100 studies on station proximity and impacts on property value, finding that the majority of them used a semi-log linear approach to their hedonic analysis. The studies we discussed in our literature review also show a pattern of using the semi-log hedonic regression.

Considering this, we have decided to use the same log-linear function due to thorough empirical research in the past. Using this function, as opposed to the simple linear function, we can sort out the percentage change in the dependent variable as a result of a one-unit increase in the independent variables. The results in this format will also be beneficial when comparing our results to previous research.

4.3 Model Specification

This study will use two base models to test our hypotheses that proximity to stations will increase property price premiums, and if the relationship is linear. One model will test the effect using the continuous distance measure, while the other will test the effect based on distance ring bands in intervals from the station. We use both models to check if the different approaches give different results. For the analysis, we will use a semi-log linear hedonic OLS regression for our purpose with the following two base models:

$$\ln PSM_i = \beta_0 + \beta_1 Distance_i + \sum_j \mu_j X_{ij} + e_i \tag{1}$$

$$\ln PSM_i = \beta_0 + \sum_j \beta_j DDist_{ij} + \sum_j \mu_j X_{ij} + e_i \tag{2}$$

Where

PSM_i = price per square meter of each transacted property i;

β_0 = constant term;

$Distance_i$ = distance (kilometers) of each property i, from the station;

$DDist_i$ = dummy variable for distance category intervals;

X_{ij} = physical characteristics j of properties, defining each property i;

e_i = error term

4.3.1 Treatment of Time

Further, to account for the perspective of time, we have decided to put our main models in two time-varying models; one where time is treated as intervals of our data sets, given as sub-data sets, and one that treats the time variables as dummies. The same approach was utilized in a study in Washington (Xu, 2015). This distinction aims to reveal possibly systematic findings that can support our hypotheses.

Development Model

For our analysis of housing price capitalization from new commuter railways, we have decided to make a development model which contains subsamples from before, during, and after the development of the commuter rail. The purpose of this model is to deem price development related to the construction of new railways. Similar to Dube et al. (2013), we have divided our data into three different time categories to compare prices before the construction started, during the building process, and after the operation of the railways started. As the railway station in Ski is not completed before December 2022, we have no observations in this city's "after" time. We still consider Ski to be an important city to include due to the shared parallels and qualities with Lillestrøm, as well as for future research purposes.

Time Dummy Model

As an extension of the base models, we have in this model included the time aspect as dummy variables in order to capture time-fixed effects for each year. The main purpose is to validate our third hypothesis. Even if we treat time differently in the two extension models, we have decided to use the same observation time periods for both cities. Lillestrøm will have transactions between 1991 and 2010, while Ski will have transactions between 2000 and 2021. The models are therefore extended with one additional term, presented below:

$$\ln PSM_i = \beta_0 + \beta_1 Distance_i + \sum_j \mu_j X_{ij} + \sum_j \tau_j DTime_{ij} + e_i \tag{3}$$

$$\ln PSM_i = \beta_0 + \sum_j \beta_j DDist_{ij} + \sum_j \mu_j X_{ij} + \sum_j \tau_j DTime_{ij} + e_i \tag{4}$$

Where

$DTime_i$ = dummy variable equaling 1 if the property was transacted in the represented year, 0 otherwise

5. Data and Descriptive Statistics

5.1 Data Collection

Through a collaboration agreement, we obtained our primary data from Virdi AS. Virdi is a platform for home buyers to evaluate home prices and keep track of real estate transactions. Virdi began their services by working for professionals but soon decided that the information should be made public in order to provide a fair playing field in the housing market for everyone. The platform was formally launched in March 2020, and users and other participants have given it excellent feedback (*Om VIRDI*, n.d.).

Secondary data for this thesis was collected from various sources, including Statistics Norway (SSB), Google Maps, and Lillestrøm and Nordre Follo municipality home pages.

5.1.1 Transaction Data

The transaction data utilized in our analysis was one of two data sets conducted from Virdi AS. This data set included all the records of sales in the respective areas we requested. It consisted of the official date of sale, the official sales price, and an ID to identify the transactions to the correct properties.

5.1.2 Address Data

The address data set was the second of the files given by Virdi. This data set provided us with all the physical aspects of the properties we use as variables in our analysis, and other important information such as coordinates, age, area, and other. This data set also included the ID to match the properties with the transactions.

5.2 Data Cleansing

To sort out our data set, we needed to combine the documents. We did so by pairing the matching ID from the address sheet with the transactions sheet using the LOOKUP function in Excel. By doing so, we had one document for each study area containing transactions and transaction dates as well as the property information regarding addresses and other property specifics.

We started our filtering process by removing all districts that were not a part of the cities, Lillestrøm and Ski. We did this as we wanted to focus on the cities in isolation. Further, we removed all commercial buildings, keeping only homes, and then removed all homes that were not private, like student housing and senior centers.

While studying our data set, we observed that we had some outliers where properties had been sold at a generous premium. These were sales related to the development of larger housing projects and therefore removed as they do not represent regular private home sales. Another observation we made was that sales of houses with separate basement apartments were recorded twice, with the same sales date and price. We removed these repetitive transactions.

The last filtering we did was removing all transactions that lacked information for one or more variables we wanted to use for our analysis. We did this to ensure we had complete data sets without any null observations.

Lastly, for some of our regressions, we divided houses and apartments in separate data sets. The houses data sets include single-family houses, duplexes, and townhouses. The apartment data sets include everything from triplexes to large apartment buildings. We did this separation to see if we could find any differences between the two categories as they usually appeal to different buyers in the market.

5.3 Variables

5.3.1 Dependent Variable

The dependent variable in our analysis is the natural logarithm of price per square meter (PSM). This metric describes how much a buyer will need to pay for each square meter of the property and is widely used to measure housing price statistics. Additionally, the PSM will make it easier to establish the “true” price on the housing market and make it easier to compare with other properties. This is similar to comparing price per kilogram for groceries at the grocery store. Due to increased inflation, we have adjusted the house prices to work with real-time home prices. We have used house price indices from Statistics Norway (SSB) to adjust the housing prices (*Prisindeks for brukte boliger*, 2021). The following equation has been used for adjustment calculation:

$$PSM_{adj} = PSM_p \times \frac{I_n}{I_p}$$

Where PSM_{adj} is the adjusted price per square meter, PSM_p is the price per square meter before adjustment, I_n is the house pricing index of 2021 and I_p is the house pricing index of the year n before adjustment.

5.3.2 Explanatory Variables

Physical Characteristics Variables

The physical characteristics considered in our model consist of floor area in square meters, lot area in square meters, number of rooms, number of bathrooms, number of toilets, number of stories in the building, age of the property, and for the apartment models; what story the apartment is on, and if the building contains an elevator or not.

Environmental Variables

We only included one environmental variable in our model; if the property is adjacent to water, such as a lake, river, or ocean. This is due to the lack of other environmental variables in our obtained data set.

Train-related Variables

As for the train-related variables, we have included both ring bands as dummy variables and a linear distance measure as an independent variable. The ring bands are measured in the intervals from 0-250 meters, 250-500 meters, 500-1000 meters, 1000-1500 meters, and everything beyond 1500 meters in the distance from the train station is being used as a reference group.

Train Distance Calculation

To measure the distance between our observations and the main point, the train station, we have used the *Haversine formula*. The Haversine formula stems from 1805 and is commonly used to accurately calculate positions on celestial bodies (Robusto, 1957). The formula considers the latitude and longitude as well as the curvature of the earth when measuring the distance between two points. By using our x-coordinates as longitude and y-coordinates as latitude for each observation, we found the distance with the following calculations:

$$d = 2rsin^{-1}\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \qquad (5)$$

Where d is the distance between two points, r is the radius of earth, φ_1 is the latitude of point one, φ_2 is the latitude of point two, λ_1 is the longitude of point one, and λ_2 is the longitude of point two.

Time-varying Variables

The time-varying variables will only appear in the Time Dummy Model as the Development Model does not include time-varying variables. These variables are included as dummy variables from 1991 – 2010 for Lillestrøm and 2000 – 2022 for Ski.

5.4 Descriptive Statistics

See Appendix A.

6. Results and Discussion

The following part will present the main findings and results of the regressions. First, we run a regression to evaluate the correlation between station proximity and housing prices. Next, the ring band distance method will be applied to assess whether there is a linear relationship between housing prices and station proximity. Finally, to determine whether the construction of new commuter rails affects housing prices, we will run two regressions with different time treatments. The significance of all variables will be displayed either in the text or appendix, but only those relevant to our research questions will be discussed as we deem necessary. All the variables are still valuable for our analysis as they contribute to improving the model.

6.1 Station Proximity

To begin, we investigate if there is a general housing price premium from station proximity. We ran regressions measuring the effect using the continuous measure method for the two cities separately, displayed in the table below.

Table 1. Station Proximity

STATION PROXIMITY						
	Lillestrøm			*Ski*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00138	3.13	0.002	-.00134	-3.80	0.000
floor_area	-.00457	-18.81	0.000	-.00348	-22.78	0.000
rooms	-.05414	-4.57	0.000	-.00693	-1.08	0.282
bathrooms	-.02612	-0.65	0.517	.01533	0.81	0.417
wc	.16270	4.86	0.000	.03662	2.26	0.024
border_water	.16327	4.42	0.000	.09810	5.78	0.000
train_dist	**-.14877**	-5.40	0.000	**-.08912**	-15.71	0.000
_cons	11.553	222.47	0.000	11.348	423.53	0.000
Adj. R^2	52.62			53.21		
N	1,096			2,017		

Note: The colors denote the significance level of 1%, 5% and 10%.

In Table 1, we observe an adjusted R^2 of 52.62% and 53.21%. Most of the coefficients were significant on all levels. The most important coefficient from these regressions is *train_dist.* This coefficient estimates the percentage change in price per square meter for each additional kilometer that separates a house from the station. The negative coefficient matches our assumption as we believe that the increased distance to stations results in an increased discount. From the findings, we observe that Lillestrøm is giving a 14.87% discount, while Ski is giving an 8.91% discount per kilometer increased distance from the stations. The results from the aggregated models show that there is a premium on station proximity. This is consistent with the previously reviewed literature (e.g., Al-Mosaind et al., 1993; Dubé et al., 2013; Ferguson, 1984; Voith, 1991).

Next, we will continue investigating our second research question, whether the relationship between housing price premiums and station proximity is linear. We are interested in uncovering if the closest location to a train station gives the highest premium or if another distance is more desirable. To test this assumption, we have applied the same model as above, replacing the continuous distance measure with ring band measures with given intervals between 0-1500 meters.

6.1.1 Ring Bands

Lillestrøm – Ring Bands

Table 2. Lillestrøm Ring Bands

PSM_LOG_ADJ	*COEFFICIENT*	*T*	*P>T*
age	.0014	3.14	0.002
floor_area	-.00455	-18.51	0.000
rooms	-.05449	-4.56	0.000
bathrooms	-.02136	-0.53	0.598
wc	.15494	4.61	0.000
border_water	.18559	4.91	0.000
less_250m	.33503	2.38	0.017
less_500m	.29042	3.98	0.000
less_1000m	.20563	3.42	0.001
less_1500m	.15766	2.64	0.008
_cons	11.2222	155.69	0.000
Adj. R^2		52.12	
N		1,096	

Note: The colors denote the significance level of 1%, 5% and 10%.

In Table 2, we acquire an adjusted R^2 of 52.12%, which is almost the same as in Table 1. This is expected as the variables are equal except for the ring band dummies that replace the train distance coefficient. We obtain strongly significant coefficients for the majority of the variables. The ring band results for Lillestrøm further validate our expectations. We obtain results showing that the housing price premium is most substantial for the closest ring band of 0-250 meters and steadily decreases as the distance increases.

As we now have established a negative linear relationship in our model, we want to see if this applies to both houses and apartments in Lillestrøm. Therefore, we distinguish between the two and run additional regressions. From our results, portrayed in Table 3 below, the new adjusted R^2 decrease some with values of 50.63% and 42.07%, for Houses and Apartments. In these regressions, we have included two additional variables, *lot_area* and *stories* for Houses and *elevator* and *story_number* for Apartments. As the additional variables contribute to explaining the housing prices, our premiums from the ring band coefficients decrease some.

Table 3. Lillestrøm Ring Bands Separated

	HOUSES			*APARTMENTS*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00114	1.99	0.047	-.00097	-1.01	0.313
floor_area	-.00504	-17.91	0.000	-.00213	-2.05	0.041
rooms	-.06634	-4.71	0.000	-.07698	-2.66	0.008
bathrooms	.03214	0.64	0.519	-.03640	-0.54	0.587
wc	.12006	2.81	0.005	.16981	3.76	0.000
elevator	-	-	-	.11756	3.28	0.001
story_nr	-	-	-	.05895	5.17	0.000
lot_area	.00007	1.17	0.244	-	-	-
stories	.03081	1.15	0.250	-	-	-
border_water	.03143	0.17	0.869	.08544	2.43	0.015
less_250m	.19515	2.65	0.008	.12840	0.63	0.529
less_500m	.31134	3.57	0.000	.02370	0.13	0.897
less_1000m	.18805	2.78	0.006	.06481	0.37	0.714
less_1500m	.23205	3.46	0.001	-.12459	-0.70	0.482
_cons	11.228	95.87	0.000	11.163	60.08	0.000
Adj. R^2	50.63			42.07		
N	728			368		

Note: The colors denote the significance level of 1%, 5% and 10%.

Looking at the table above, we do not receive any significant ring band coefficients for Apartments. However, when assessing Lillestrøm Houses, the results displayed contradicts our hypothesis slightly. Like Bowes and Ihlanfeldt (2001) found, houses located within the second interval, 250-500 meters, gave the highest premium from station proximity. One explanation for this could be what Bowes and Ihlanfeldt (2001) emphasized in parts of their study, that crime and gang activities around the train stations could lead to a desire to not live within the closest ring bands. In Lillestrøm, several crime-related incidents have been reported near the train station, such as robbery, drug distribution, and fights (Blad, 2015; Karlsen, 2021; Vinningland, 2022). However, as we do not include any explanatory variables on this aspect in *our* model, it can be difficult to establish such a statement, and future research on this could be helpful.

Another possible reason for the decreased premium in the closest ring band could be other negative effects such as noise pollution and vibrations (Armstrong & Rodríguez, 2006; Strand & Vågnes, 2001). In Strand & Vågnes's study, they found negative effects on housing prices up to 100 meters from the railroad, mainly due to noise disturbances. However, it can be difficult to compare as Strand & Vågnes based their study on proximity to railroads in general and not train stations. It could be reasonable to assume that a train station will have lower volume levels and vibrations due to reduced speed as the train approaches the station.

Ski – Ring Bands

Next, we continued with Ski. For the ring band model for Ski, the reported adjusted R^2 is 50.28%, displayed below in Table 4. These results show that the highest premium is obtained from the closest proximity, the 0–250-meter ring band. However, for the two following bands, 250-500 meters, and 500-1000 meters, the premiums are almost the same. The 500-1000-meter ring band obtains a 2.4 percentage points larger premium. This is a slight contradiction to our expectation of the linear relationship.

Table 4. Ski Ring Bands

PSM_LOG_ADJ	*COEFFICIENT*	*T*	*P>T*
age	-.00240	-6.73	0.000
floor_area	-.00355	-22.30	0.000
rooms	-.00739	-1.11	0.268
bathrooms	.00663	0.34	0.736

wc	.04439	2.64	0.008
border_water	.08365	4.69	0.000
less_250m	.42523	6.41	0.000
less_500m	.20234	7.57	0.000
less_1000m	.22624	9.84	0.000
less_1500m	.15588	7.10	0.000
_cons	11.117	313.95	0.000
Adj. R^2		50.28	
N		2,017	

Note: The colors denote the significance level of 1%, 5% and 10%.

We want to investigate this contradiction further by dividing houses and apartments in Ski as well to see if we find any distinctions in the results for the different housing types. The result for this regression is presented in Table 5 below. The results for apartments are as expected, with a steadily decreasing premium for decreased proximity. However, for houses, we only obtain significant results for the two ring bands with the largest distance, 500-1000 meters, and 1000-1500 meters. The significant result does, however, present a higher premium for the closest ring band of the two, supporting our expectation.

Table 5. Ski Ring Bands Separated

	HOUSE			*APARTMENTS*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	-.00168	-3.24	0.001	-.00267	-5.96	0.000
floor_area	-.00369	-16.87	0.000	-.00316	-7.13	0.000
rooms	-.01707	-1.80	0.073	.01046	0.93	0.355
bathrooms	-.00228	-0.08	0.934	-.00171	-0.06	0.950
wc	.01202	0.53	0.594	.14376	6.08	0.000
elevator	-	-	-	.02238	1.41	0.160
story_nr	-	-	-	.01643	3.82	0.000
lot_area	-.00002	-2.66	0.008	-	-	-
stories	.02733	1.60	0.109	-	-	-
border_water	.22394	3.38	0.001	.06099	4.60	0.000
less_250m	0			.43667	5.68	0.000
less_500m	.01209	0.24	0.813	.29955	4.37	0.000
less_1000m	.23292	7.55	0.000	.26451	3.88	0.000
less_1500m	.15859	5.61	0.000	.21363	3.10	0.002
_cons	11.209	193.19	0.000	10.823	150.83	0.000
Adj. R^2	34.14			27.32		
N	1,171			846		

Note: The colors denote the significance level of 1%, 5% and 10%.

After conducting all our ring band regressions, we question the impact centrality has on the housing prices we have assessed. Both Lillestrøm and Ski have several amenities that will affect prices in the area, such as job offers, restaurants, shops, nightlife, and others. This makes the cities attractive places to live both for younger working people and families with children. The quality of the cities and the house price premiums do not only come from the accessibility to Oslo but also from the centrality that comes with internal factors from the cities. Landis et al. (1994) emphasized how other external factors to the properties contributed to housing price premiums in addition to station proximity. To further investigate the centrality effect, we measured the distance from the train stations to the town squares in the respective cities. We found that the ring band with the highest premium in both cities was also the ring band where the town square is located. For Lillestrøm, this was the second ring band, 250-500 meters, and the first ring band, 0-250 meters, for Ski. This could be an indication of the centrality effect as the highest premiums match with the location of the amenities.

In addition to the centrality effect, another external attribute could be what Duncan (2011) mentions in his study. He found evidence that premiums from station proximity were higher where the station was located in a pedestrian-oriented environment. This applies to Lillestrøm and Ski as they are pedestrian-friendly cities where their stations are easily accessible without auto transportation. Both cities aim to be leading "bike towns," which underscores Duncan's (2011) argument about being less car dependent and relying on more sustainable transportation methods (Ski Kommune, 2019; *Sykkelkommunen Lillestrøm*, n.d.). Therefore, some of the housing price premium might be due to these factors.

6.2 Development Model

In this section, we target our last research question of the effect new development of commuter rails has on housing prices as well as the distance impact. Here, we will present all development models for each city. We have decided to continue with the separation of houses and apartments as this will give a more holistic view. We have run regressions with both distance methods but have decided to only present the ring band distance results in this section. Thus, the continuous distance measure will be present in Appendix B. The time periods used are *Before, During,* and *After* for Lillestrøm and *Early, Before,* and *During* for Ski to best fit the development of the respective commuter rails. The reference group used for all ring band regressions is every observation beyond 1500 meters from the station.

6.2.1 Lillestrøm Houses

Table 6. Lillestrøm Ring Bands Development – Houses

	BEFORE 1991-1994			*DURING 1995-1999*			*AFTER 2000-2010*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	-.00635	-1.90	0.063	.00347	1.99	0.049	.00121	2.05	0.041
lot_area	-.00017	-0.50	0.617	.00007	0.82	0.412	.00031	3.57	0.000
floor_area	-.00421	-4.46	0.000	-.00479	-5.43	0.000	-.00516	-17.38	0.000
rooms	-.03179	-0.56	0.579	-.14514	-3.41	0.001	-.04604	-3.12	0.002
bathrooms	-.19511	-0.58	0.568	.15477	1.20	0.231	.00097	0.02	0.985
wc	.10461	0.37	0.714	.11680	0.98	0.331	.11495	2.63	0.009
border_wat	0			0			-.00813	-0.05	0.963
stories	-.21155	-1.82	0.074	.14994	1.89	0.061	.02753	0.99	0.321
less_250	.65288	1.01	0.315	0			.22923	2.41	0.017
less_500	.32665	0.88	0.382	-.02007	-0.07	0.947	.38041	4.15	0.000
less_1000	.43813	1.56	0.126	-.24632	-0.88	0.379	.24897	3.68	0.000
less_1500	.42722	1.56	0.125	-.06595	-0.24	0.811	.28340	4.23	0.000
_cons	12.2713	22.3	0.000	11.0780	29.5	0.000	11.0606	88.83	0.000
Adj.R^2	0.4737			0.5085			0.5525		
N	61			126			541		

Note: The colors denote the significance level of 1%, 5% and 10%.

In Table 6, we observe an adjusted R^2 of 47.37%, 50.58%, and 55.25%. Despite the acceptable adjusted R^2's, we only obtain significant coefficients of interest in the period *After*. Here, the ring bands validate our previous findings on station proximity and housing prices. However, the time aspect of the models is hard to assess from this data set as we get very few significant coefficients for *Before* and *During*. We also get no significant results for our distance measurements, and we can only assess this matter in *After*.

Similar to the findings in the ring band section for Lillestrøm Houses, we obtain the highest price premium of 38.04% in the second ring band, 250-500 meters. These findings validate our hypothesis about positive capitalization for houses with proximity to stations and is consistent with Bowes and Ihlanfeldt (2001). However, we see a 3.44% decrease in the premium for houses in the ring band of 500-1000 meters compared to houses in the 1000-1500 meters ring band. This does not support our hypothesis about the steadily increased discount with decreased proximity.

6.2.2 Lillestrøm Apartments

Table 7. Lillestrøm Ring Bands Development – Apartments

	BEFORE 1991-1994			*DURING 1995-1999*			*AFTER 2000-2010*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age				.03784	2.55	0.025	-.00274	-2.96	0.003
elevator				.97273	2.52	0.027	.09568	2.79	0.006
story_nr				-.09774	-1.13	0.279	.04765	4.47	0.000
floor_area				-.00315	-0.27	0.794	-.00215	-1.93	0.055
rooms				-.10142	-0.45	0.662	-.06498	-2.24	0.026
bathrooms				-.02624	-0.06	0.954	.06151	0.92	0.359
wc				-.25034	-0.80	0.440	.17942	4.24	0.000
border_wat				-.24007	-0.89	0.392	.11137	3.36	0.001
less_250				0			0		
less_500				.3183	1.07	0.304	-.15003	-1.42	0.155
less_1000				-.22831	-0.72	0.486	-.09803	-1.01	0.313
less_1500				-.36034	-1.68	0.119	-.21371	-2.14	0.033
_cons				11.0780	22	0.000	11.2338	97.60	0.000
Adj. R^2	0			0.4310			0.5525		
N	7*			24			337		

Note: The colors denote the significance level of 1%, 5% and 10%. *This interval could not be regressed as there were only seven observations.

For apartments in Lillestrøm, we did not have enough observations for the *Before* time period to conduct a regression. Therefore, this column is empty. There were also no observations within the 250 meters ring band, and the row is presented with a coefficient of zero. The adjusted R^2 in Table 7 is 43.10% and 55.25%. We have few observations for *During*, only 24. For *After,* we have a considerably larger sample with an observation number of 337. This leads to an increased number of significant results. However, for this data set, the ring bands only show significant results for the largest band of 1000-1500 meters. These results do not support our hypothesis as it suggests that housing prices will receive a discount of 21.37% from the given level of station proximity compared to the reference group.

When looking at our Development Model for Lillestrøm Houses and Apartments, obtaining significant outcomes in all time periods was challenging. This makes it difficult to determine whether house prices have improved during the construction of new railways.

6.2.3 Ski Houses

Table 8. Ski Ring Bands Development – Houses

	EARLY 2000 - 2009			*BEFORE* January 2010 – June 2015			*DURING* June 2015 – March 2022		
PSM_log_a	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00313	1.86	0.065	-.00195	-1.14	0.255	-.00179	-3.38	0.001
lot_area	-4.29e-06	-0.07	0.943	-5.46e-06	-0.24	0.808	-.00002	-2.95	0.003
floor_area	-.00487	-6.02	0.000	-.00309	-5.44	0.000	-.00355	-15.65	0.000
rooms	-.02114	-0.78	0.435	-.0176	-0.69	0.490	-.0071	-0.69	0.492
bathrooms	-.12336	-1.46	0.145	-.05157	-0.69	0.489	.02518	0.83	0.407
wc	.0590	0.76	0.448	-.03686	-0.51	0.608	-.00418	-0.19	0.852
border_wat	.23715	0.91	0.363	.29099	1.70	0.091	.16142	2.40	0.017
stories	.04555	0.70	0.487	.03722	0.75	0.455	.04883	2.69	0.007
less_250	0			0			0	-	-
less_500	.11908	0.75	0.454	.04116	0.31	0.757	.09861	1.76	0.079
less_1000	.44394	4.19	0.000	.38638	4.13	0.000	.20196	6.36	0.000
less_1500	.2963	2.49	0.014	.43525	4.86	0.000	.11145	3.97	0.000
_cons	11.0167	55.6	0.000	11.079	64.6	0.000	11.1527	176.00	0.000
Adj. R^2	0.2879			0.4149			0.3795		
N	193			222			756		

Note: The colors denote the significance level of 1%, 5% and 10%.

Table 8 presents an adjusted R^2 of 28.79%, 41.49%, and 37.95%, respectively. R^2 appears to be lower for the regressions of Ski compared to Lillestrøm. Nevertheless, we still get several significant results.

We observe from all three time periods that the ring bands capitalize positively on the house prices. None of the time periods observed house sales within the 250 meters band, therefore zero. In the next band, 250-500 meters, only *During* showed significant results, with a premium of 9.86%. For *Early* and *During,* the 500-1000 meters ring band has the highest premium of 44.39% and 20.20%. For *Before,* the ring band of 1000-1500 meters presented the largest premium of 43.53%. To further evaluate these findings in terms of time, we see that the premium effect of station proximity is decreasing. The premium for the ring bands is at its highest in *Early* and decreases for the following time periods. This implies that the development of the new commuter rail does not result in an increased premium and contradicts our hypothesis.

A reason for the decreasing price premiums could be negative externalities, such as noise pollution and industrialization, connected to an extensive construction period of more than seven years. This may have made Ski a less desirable city to reside in

(Armstrong & Rodríguez, 2006; Bowes & Ihlanfeldt, 2001). In combination with this, the accessibility of residents in Ski might not depend on the commuter rail. Like Gatzlaff and Smith (1993) suggest, suburbs located in proximity to highways are in less need of alternatives to increase their accessibility. As Ski is located next to the European routes E6 and E18, this city may fall into this category.

6.2.4 Ski Apartments

Table 9. Ski Ring Bands Development – Apartments

	EARLY *2000 – 2009*			*BEFORE* *January 2010 – June 2015*			*DURING* *June 2015 – March 2022*		
PSM_log_a	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	-.00012	-0.02	0.984	-.00522	-2.38	0.018	-.0022	-5.03	0.000
elevator	-.06251	-0.77	0.444	-.04341	-1.61	0.108	.02435	1.37	0.171
story_nr	.06812	2.52	0.014	.03937	5.07	0.000	.00636	1.39	0.164
floor_area	-.00075	-0.30	0.765	-.0007	-0.96	0.336	-.00405	-8.47	0.000
rooms	.02322	0.36	0.716	.02661	1.25	0.211	.00168	0.14	0.888
bathrooms	.06462	0.62	0.538	-.04028	-1.04	0.302	.01796	0.53	0.600
wc	-.05411	-0.53	0.597	.05584	1.73	0.086	.16761	5.65	0.000
border_wat	.06602	0.84	0.404	.04425	1.30	0.195	.06178	4.57	0.000
less_250	0			.68934	5.05	0.000	.29759	3.20	0.001
less_500	.01974	0.21	0.837	.51261	5.38	0.000	.15018	2.03	0.042
less_1000	.05284	0.30	0.769	.51773	5.29	0.000	.18126	2.48	0.013
less_1500	.30305	0.92	0.358	.41935	4.14	0.000	.11311	1.54	0.124
_cons	11.0118	42.6 3	0.000	10.5996	89.1 6	0.000	10.9506	142.53	0.000
Adj. R^2	-0.0056			0.3320			0.3395		
N	95			217			534		

Note: The colors denote the significance level of 1%, 5% and 10%.

We see from Table 9 that the adjusted R^2 for *Early* is -0.056%. We will therefore not assess the results from this regression. For the additional regressions, we get an adjusted R^2 of 33.20% and 33.95% from *Before* and *During*. For the regressions related to apartments in Ski, we get significant distance results for the same time periods.

In *Before* and *During*, the results show that the premium is largest for the apartments closest to the station, with a premium of 68.93% and 29.76%. The premium for the following two ring bands is essentially the same, with 51.26% for 250-500 meters and 51.77% for 500-1000 meters in *Before*. In *During,* the premium is 15.02% and 18.13% for the same two bands. Lastly, the 1000-1500-meter ring band presents a premium of 41.94% for *Before.* For *During,* the result is not significant for this band.

One issue observed from apartments in Ski is the high premiums we obtain from the regressions. The results indicate unusually high premiums in *Before,* e.g., 68.93% for the 250-meter ring band. In this time period, we had some particularly expensive apartments in the city center in Ski, which is believed to contribute to these high results.

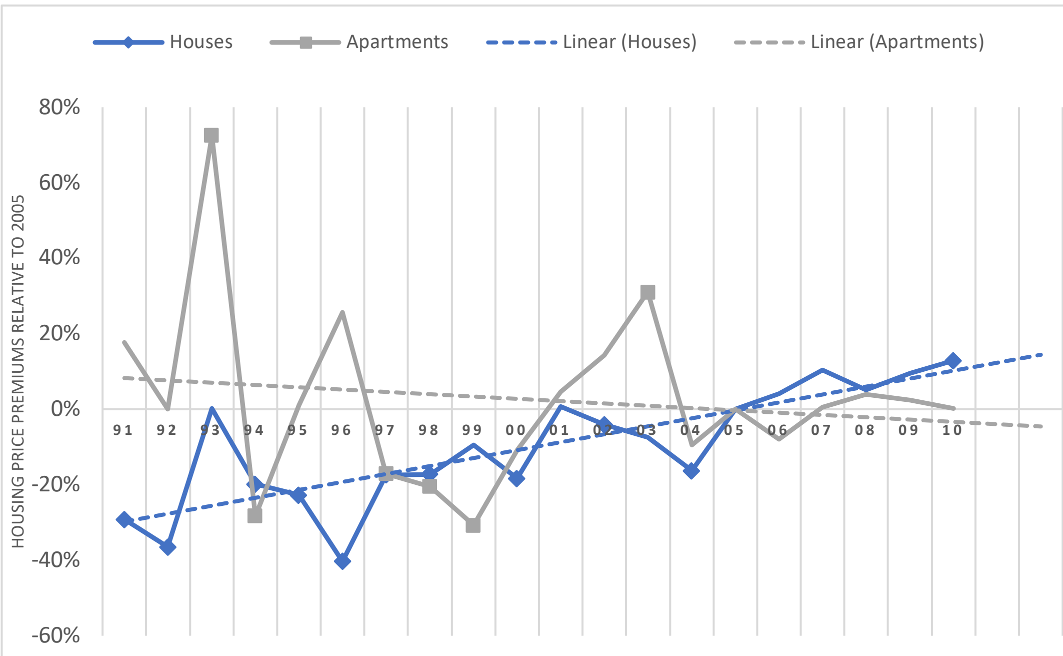
6.3 Time Dummy Model

This section will present time dummy models for each city and the two housing groups for the ring bands. As earlier mentioned, the purpose of the time dummy model is to investigate if systematic patterns can be found in the data as an additional tool to the Development Model. The reference group for all ring band regressions was every observation beyond 1500 meters from the station.

We begin by running the regressions for our extended model. We separate houses and apartments once again to distinguish between possible differences. As the time aspect in this model is our primary focus, we display our time dummy coefficients from our regression in Figure 1 and Figure 2 in this section and move our tables with the total results to Appendix B, section 2.

6.3.1 Lillestrøm

Figure 1. Time Dummy Evolution in Lillestrøm



Note: Figure 1 displays all time dummies. Significant results marked with points in the graph. The reference year used is 2005 for both Houses and Apartments.

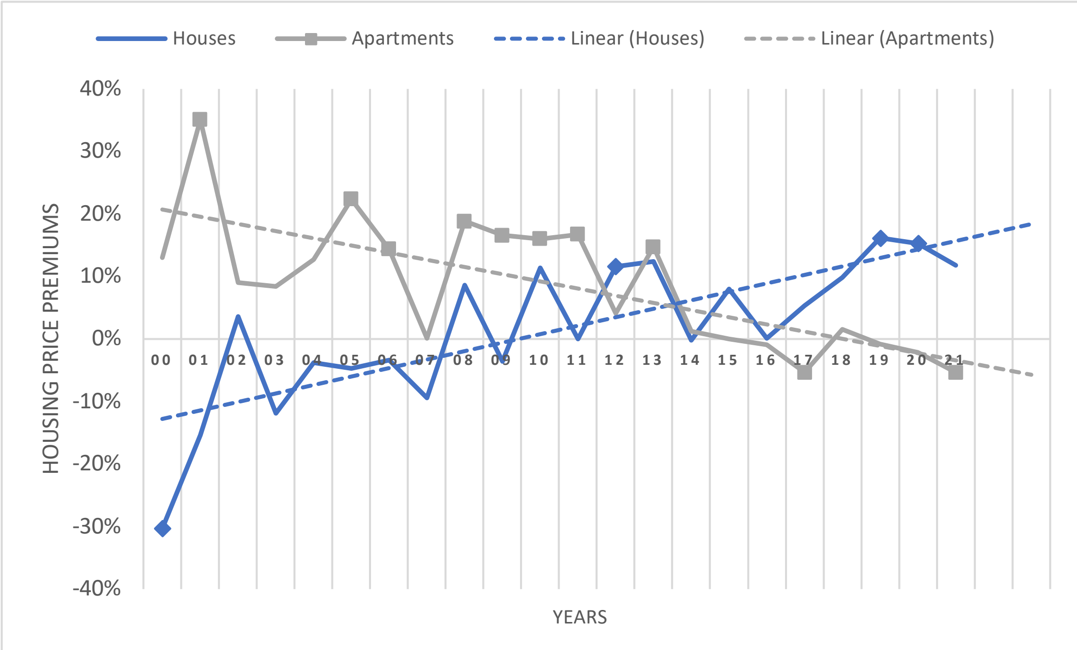
When studying the findings from Lillestrøm in Figure 1, we can observe the plotted outcome of our time dummy regression and a linear housing price trend given from these results. Half of the dummy coefficients for houses give significant values, while apartments only give a few. However, as the significant dummies are evenly spread across the graph, it may be possible to observe a trend. For houses in Lillestrøm, we see a trend of increasing housing prices with time, which is consistent with our expectations.

On the other hand, the trend for apartments appears to be decreasing with time. This could potentially be due to the big spike in 1993. As this year generated a very high premium, we decided to look at our data set. Here, we observed that this particular year included abnormally high transaction prices along with few observations. The trend could have been different if this year was to be excluded. Hence, it is reasonable to assume that these results are not representative.

As we did not receive enough presentable results for Lillestrøm Houses and Apartments in the Development Model, as examined in sections 6.2.1 and 6.2.2, we cannot draw any conclusions. From the Time Dummy Model, the trend could be increasing for the time period chosen, but our total time analysis does not generate enough to make this assumption true. Hence, we cannot validate our hypothesis about increased housing price premiums with the development of new commuter rails for Lillestrøm.

6.3.2 Ski

Figure 2. Time Dummy Evolution in Ski



Note: Figure 2 displays all time dummies. Significant results marked with points in the graph. The reference year used is 2011 for Houses and 2015 for Apartments.

Even though the model for houses in Ski has the largest number of observations, 1,171, we obtain very few significant time dummy coefficients displayed in Figure 2. This makes it hard to assess the time perspective based on the time dummy model. By only assessing the significant time dummies from 2000, 2012, 2019, and 2020, an increasing price premium tendency can be observed. However, as almost all the years in between are insignificant, it is difficult to establish any trends.

For apartments, we obtain a sufficient number of significant coefficients resulting in a visible trend of decreasing housing prices over time. This is consistent with the decreasing trend we found in the development model and continues to contradict our hypothesis. We obtain favorable premiums during all periods, but unlike Ferguson (1984), the premium is shown to be highest even before the building period took place. Hence, the results display dropping premiums in the construction period.

As the results for Ski Apartments are unique, we decided to take a deeper look into this particular data set. An interesting observation was that more than 50% of the apartments closest to the station were sold in the years 2003 and 2004 and have not been resold since. These apartments are considered valuable, with a house price increase of 323% and 303% calculated through the Housing Price Index for 2021, utilized throughout our thesis. With homeowners holding onto their properties for an extended period of time, important observations in the latest period of the data set are not included. Thus, there may be a perception of higher price premiums in the earliest time period.

Lastly, as the Time Dummy Model was included as a different manner of classifying our data, the results were intriguing. The results came with various significances but mainly confirmed what the Development Model already had generated. The most interesting takeaway from this model was that it validated the findings stated in the earlier section, 6.2.4, of decreasing price premiums for Ski Apartments over time. This amplifies the contradiction of our last hypothesis.

7. Conclusion

This thesis examines the relationship between station proximity and housing prices, and the effect of developing new commuter rails. More specifically, we use a hedonic pricing log-linear model to analyze Lillestrøm and Ski over an extensive time period of nearly 20 years. We utilize a detailed data set of property transactions from Virdi AS, including coordinates as well as a number of physical parameters. Further, we distinguish between a station proximity model and two time-varying models. We have one where time is treated as intervals of our data sets, given as sub-data sets, and one that treats the time variables as dummies. By doing so, we have been able to obtain results of relevance from different approaches. Our results show that station proximity in the suburbs of Oslo yields a housing price premium. However, the analysis displays conflicting results regarding increased discounts with decreased proximity. Furthermore, we cannot establish a clear relationship between increased housing prices and development of new commuter rails.

Through our analysis, we found evidence on several occasions that station proximity led to a capitalization of housing prices. We found supporting results from both distance measures that were consistent with premiums. When assessing the continuous train distance coefficient from our first regressions, the results showed a 14.87% discount for Lillestrøm and an 8.91% discount for Ski, for every kilometer the distance increases in our respective cities. Our first hypothesis is therefore found to be true based on our general results. In combination with earlier research that finds evidence for the same conclusion, we find it factual that station proximity capitalizes on housing prices (Al-Mosaind et al., 1993; Dubé et al., 2013; Ferguson, 1984; Voith, 1991).

After establishing the relationship between station proximity and housing price premium, we continued with our second hypothesis. To validate this hypothesis, we ran the same regressions with distance ring bands included as dummies instead. Here, we found contradicting results running the ring band model. The results from these tests showed that the relationship is, in fact, not always linear. For Lillestrøm, like Bowes and Ihlanfeldt (2001), houses did not give a linear relationship, with the second ring band giving the highest premium. Apartments did not give significant results, and we could therefore not conclude here. Ski, however, portrayed a linear relationship for both houses and apartments. Resultingly, different ring bands gave different levels of premiums, and we could not reach an unambiguous conclusion.

Moving on to the last research question of our thesis, we could not find results to answer it through the test of our third hypothesis. The two different time-varying models did not find results supporting a noticeable increase in premiums from the development of the new commuter rails. As already emphasized, few observations and insignificant results for Lillestrøm made it harder for us to find evidence to validate our third hypothesis. Nevertheless, the results obtained from Ski showed opposite results from what we expected. The trend we observed from our significant results was a decrease in the housing prices during the construction period of the new station and commuter rail. However, as the new commuter rail operation has not started, we have no *After*-observations for Ski. As the result from Lillestrøm does not give us significant results, it is also hard to make predictions for a possible future trend in Ski. Hence, this trend may be subject to change.

We have learned through our research and the results that the lack of extrinsic factors limited our analysis. We believe that these extrinsic factors have great importance on housing prices and that our analysis is missing important variables to explain price changes. In addition to the increased number of variables, an increased number of observations could also be beneficial to obtaining better results.

As for future research, we discussed Hønefoss as a possible city when deciding on our study area. We believe this place could be a great candidate for future research as there are plans to build a new commuter rail between Hønefoss and Sandvika, making the travel time to Oslo central station a 35-minute commute (*Ringeriksbanen*, 2022). It would also be interesting to see if it is possible to use our methods and models to forecast how the new commuter rail will affect housing prices in Ringerike district.

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Appendices

Appendix A – Descriptive Statistics

A.1 Station Proximity

Table A.1.1. Descriptive Statistics Lillestrøm Station Proximity

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	1,096	10.86033	.5536124	8.630411	13.1675
age	1,096	54.08498	31.6537	11.55068	120.1205
floor_area	1,096	135.4799	77.24741	20	473
rooms	1,096	3.997263	1.539434	1	13
bathrooms	1,096	1.187044	.4648916	1	5
wc	1,096	1.328467	.5950725	1	5
border_water	1,096	.1733577	.378729	0	1
train_dist	1,096	.9761681	.4385444	.2188379	4.663333
less_250m	1,096	.0082117	.0902867	0	1
less_500m	1,096	.0666058	.249452	0	1
less_1000m	1,096	.4625912	.4988262	0	1
less_1500m	1,096	.4206204	.493884	0	1
over_1500m	1,096	.0419708	.200614	0	1

Table A.1.2. Descriptive Statistics Ski Station Proximity

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	2,017	10.81584	.4322215	7.611658	11.86611
age	2,017	28.80122	23.56597	.4246575	119.3315
floor_area	2,017	132.5191	70.1623	26	549
rooms	2,017	4.251363	1.526479	1	12
bathrooms	2,017	1.373327	.5712546	1	4
wc	2,017	1.620228	.7109876	1	5
border_water	2,017	.2741696	.4462055	0	1
train_dist	2,017	1.225914	1.224435	.1612382	7.821084
less_250m	2,017	.0118989	.1084579	0	1
less_500m	2,017	.1601388	.3668257	0	1
less_1000m	2,017	.2821021	.4501344	0	1
less_1500m	2,017	.4129896	.4924931	0	1
over_1500m	2,017	.1328706	.339519	0	1

Table A.1.3. Descriptive Statistics Lillestrøm Ring Bands Houses

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	728	10.71532	.5885369	8.630411	12.63842
age	728	67.47972	28.22348	11.55068	120.1205
lot_area	728	648.5069	271.4756	126	4113
floor_area	728	165.2459	77.04784	28	473
rooms	728	4.502747	1.542606	1	13
bathrooms	728	1.245879	.5310026	1	5

wc	728	1.391484	.658692	1	5
stories	728	2.784341	.5924113	1	4
border_water	728	.0068681	.0826459	0	1
less_250m	728	.0041209	.0641057	0	1
less_500m	728	.0659341	.2483374	0	1
less_1000m	728	.3942308	.4890208	0	1
less_1500m	728	.4752747	.4997316	0	1
over_1500m	728	.0604396	.2384633	0	1

Table A.1.4. Descriptive Statistics Lillestrøm Ring Bands Apartments

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	368	11.14713	.3227519	9.67	13.17
age	368	27.58641	18.75065	12.12	75.52
floor_area	368	76.59511	28.46072	20	278
rooms	368	2.997283	.9205455	1	6
bathrooms	368	1.070652	.2565918	1	2
wc	368	1.203804	.4166647	1	3
elevator	368	.5	.5006807	0	1
story_nr	368	2.266304	1.192509	1	7
border_water	368	.5027174	.5006733	0	1
less_250m	368	.0163043	.1268157	0	1
less_500m	368	.0679348	.2519765	0	1
less_1000m	368	.5978261	.4910043	0	1
less_1500m	368	.3125	.4641435	0	1
over_1500m	368	.0054348	.0736205	0	1

Table A.1.5. Descriptive Statistics Lillestrøm Ring Bands Apartments

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	1,171	10.61796	.4494505	7.611658	11.86611
age	1,171	36.20238	25.5342	.4246575	119.3315
lot_area	1,171	969.7451	1448.983	95	14669
floor_area	1,171	173.0786	64.10451	68	549
rooms	1,171	5.151153	1.261611	1	12
bathrooms	1,171	1.517506	.6367594	1	4
wc	1,171	1.890692	.7303017	1	5
stories	1,171	1.972673	.7674609	1	4
border_water	1,171	.0350128	.1838907	0	1
less_250m	1,171	0	0	0	0
less_500m	1,171	.0614859	.2403221	0	1
less_1000m	1,171	.2826644	.450487	0	1
less_1500m	1,171	.4321093	.4955811	0	1
over_1500m	1,171	.2237404	.4169281	0	1

Table A.1.6. Descriptive Statistics Lillestrøm Ring Bands Apartments

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_ad~d	846	11.08975	.1913699	9.578329	11.71901
age	846	18.55682	15.53127	1.49863	74.2137
floor_area	846	76.37825	24.88979	26	194

rooms	846	3	.8284869	1	6
bathrooms	846	1.173759	.3853185	1	3
wc	846	1.245863	.4752583	1	3
elevator	846	.5390071	.498771	0	1
story_nr	846	2.562648	1.423463	1	8
border_water	846	.6052009	.4890966	0	1
less_250m	846	.0283688	.1661223	0	1
less_500m	846	.2966903	.457069	0	1
less_1000m	846	.2813239	.4499111	0	1
less_1500m	846	.3865248	.4872412	0	1
over_1500m	846	.0070922	.0839657	0	1

A.2 Development Model

Lillestrøm Houses

Table A.2.1. Descriptive Statistics Lillestrøm Before

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			Before		
PSM_log_adj	61	10.56885	.6852482	8.966353	12.00196
age	61	71.00858	23.10407	28.17534	110.6466
lot_area	61	736.7541	204.6559	231	1400
floor_area	61	164.3934	90.11479	43	445
rooms	61	4.278689	1.582521	1	10
bathrooms	61	1.229508	.4240064	1	2
wc	61	1.278689	.5206133	1	3
train_dist	61	1.086006	.4255649	.2188379	3.410241
less_250m	61	.0163934	.1280369	0	1
less_500m	61	.0655738	.2495898	0	1
less_1000m	61	.3442623	.4790701	0	1
less_1500m	61	.5081967	.5040817	0	1
over_1500m	61	.0655738	.2495898	0	1
border_water	61	0	0	0	0
stories	61	2.786885	.6086804	1	4

Table A.2.2. Descriptive Statistics Lillestrøm During

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			During		
PSM_log_adj	126	10.57122	.6315217	8.731568	12.63842
age	126	70.91924	24.93238	23.50411	120.1205
lot_area	126	687.0794	480.748	146	4113
floor_area	126	164.4444	73.47245	31	389
rooms	126	4.587302	1.449247	1	9
bathrooms	126	1.222222	.5781196	1	5
wc	126	1.396825	.6821069	1	5
train_dist	126	.985854	.3534308	.3409111	3.335852
less_250m	126	0	0	0	0
less_500m	126	.0952381	.2947154	0	1
less_1000m	126	.3888889	.4894441	0	1
less_1500m	126	.4920635	.5019328	0	1

over_1500m	126	.0238095	.1530639	0	1
border_water	126	0	0	0	0
stories	126	2.865079	.5269258	1	4

Table A.2.3. Descriptive Statistics Lillestrøm After

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			After		
PSM_log_adj	541	10.7654	.5586136	8.630411	12.61771
age	541	66.28075	29.38707	11.55068	119.0658
lot_area	541	629.573	198.6987	126	1849
floor_area	541	165.5287	76.41937	28	473
rooms	541	4.508318	1.559447	1	13
bathrooms	541	1.253235	.5310835	1	4
wc	541	1.402957	.6668823	1	4
train_dist	541	1.062289	.521873	.2430288	4.663333
less_250m	541	.0036969	.0607455	0	1
less_500m	541	.0591497	.236123	0	1
less_1000m	541	.4011091	.4905766	0	1
less_1500m	541	.4676525	.4994143	0	1
over_1500m	541	.0683919	.2526508	0	1
border_water	541	.0092421	.0957793	0	1
stories	541	2.76525	.6042851	1	4

Lillestrøm Apartments

Table A.2.4. Descriptive Statistics Lillestrøm Before

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			Before		
PSM_log_adj	7	11.06174	.7526103	10.23144	12.27027
age	7	49.33033	16.46374	36.10411	72.16164
elevator	7	0	0	0	0
story_nr	7	1.571429	.7867958	1	3
floor_area	7	107.1429	80.47034	41	278
rooms	7	3.714286	1.380131	2	6
bathrooms	7	1.285714	.48795	1	2
wc	7	1.285714	.48795	1	2
train_dist	7	.9523554	.1010847	.842575	1.151059
less_250m	7	0	0	0	0
less_500m	7	0	0	0	0
less_1000m	7	.7142857	.48795	0	1
less_1500m	7	.2857143	.48795	0	1
over_1500m	7	0	0	0	0
border_water	7	.2857143	.48795	0	1

Table A.2.5. Descriptive Statistics Lillestrøm During

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			During		
PSM_log_adj	24	10.82584	.3206144	10.23164	11.31679
age	24	29.96986	5.382773	24.37808	39.11781
elevator	24	.2083333	.4148511	0	1
story_nr	24	1.75	.7939992	1	3
floor_area	24	81.91667	27.10995	48	142
rooms	24	3.375	.8753881	2	5
bathrooms	24	1.25	.4423259	1	2
wc	24	1.291667	.5500329	1	3
train_dist	24	1.043898	.2682315	.4817961	1.55318
less_250m	24	0	0	0	0
less_500m	24	.0833333	.2823299	0	1
less_1000m	24	.2083333	.4148511	0	1
less_1500m	24	.625	.4945354	0	1
over_1500m	24	.0833333	.2823299	0	1
border_water	24	.125	.337832	0	1

Table A.2.6. Descriptive Statistics Lillestrøm After

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			After		
PSM_log_adj	337	11.17185	.2973129	9.671189	13.1675
age	337	26.96532	19.14539	12.11781	75.52055
elevator	337	.5311573	.4997703	0	1
story_nr	337	2.317507	1.211339	1	7
floor_area	337	75.5816	26.38768	20	193
rooms	337	2.95549	.9035847	1	6
bathrooms	337	1.053412	.2251889	1	2
wc	337	1.195846	.4048596	1	3
train_dist	337	.8100833	.2509218	.2461064	1.480574
less_250m	337	.0178042	.1324357	0	1
less_500m	337	.0682493	.2525481	0	1
less_1000m	337	.6231454	.4853186	0	1
less_1500m	337	.2908012	.4548073	0	1
over_1500m	337	0	0	0	0
border_water	337	.5341246	.4995759	0	1

Ski Houses

Table A.2.7. Descriptive Statistics Ski Early

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			Early		
PSM_log_adj	193	10.46023	.5872806	8.129758	11.75833
age	193	40.57067	22.94933	12.27123	110.1233

lot_area	193	946.1832	660.9138	106	4703
floor_area	193	182.5803	62.05001	69	353
rooms	193	5.082902	1.62768	1	12
bathrooms	193	1.523316	.6214276	1	4
wc	193	1.860104	.7115959	1	4
train_dist	193	1.452422	1.560027	.2981405	7.798228
less_250m	193	0	0	0	0
less_500m	193	.0880829	.2841525	0	1
less_1000m	193	.4145078	.4939181	0	1
less_1500m	193	.3005181	.4596758	0	1
over_1500m	193	.1968912	.3986836	0	1
border_water	193	.0207254	.142834	0	1
stories	193	2.336788	.6337258	1	4

Table A.2.8. Descriptive Statistics Ski Before

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			Before		
PSM_log_adj	222	10.63586	.4997789	7.96133	11.74269
age	222	27.7611	21.17186	7.126027	117.1123
lot_area	222	864.8847	1533.242	96	14669
floor_area	222	177.7162	73.7659	68	549
rooms	222	5.36036	1.25336	3	9
bathrooms	222	1.801802	.6284337	1	4
wc	222	2.004505	.6416731	1	4
train_dist	222	1.454668	1.444922	.2577406	7.700654
less_250m	222	0	0	0	0
less_500m	222	.0810811	.2735765	0	1
less_1000m	222	.2387387	.4272762	0	1
less_1500m	222	.536036	.4998267	0	1
over_1500m	222	.1441441	.3520296	0	1
border_water	222	.0405405	.1976689	0	1
stories	222	2.310811	.6074725	1	4

Table A.2.9. Descriptive Statistics Ski During

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			During		
PSM_log_adj	756	10.65296	.3801819	7.611658	11.86611
age	756	37.56599	26.78696	.4246575	119.3315
lot_area	756	1006.553	1565.143	95	14669
floor_area	756	169.291	61.25779	68	415
rooms	756	5.107143	1.147598	1	11
bathrooms	756	1.43254	.619292	1	4
wc	756	1.865079	.7566378	1	5
train_dist	756	1.590473	1.497734	.2700151	7.821084

less_250m	756	0	0	0	0
less_500m	756	.0489418	.2158892	0	1
less_1000m	756	.2619048	.4399622	0	1
less_1500m	756	.4351852	.4961095	0	1
over_1500m	756	.2539683	.4355678	0	1
border_water	756	.037037	.1889776	0	1
stories	756	1.780423	.7733562	1	4

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Table A.2.10. Descriptive Statistics Ski Early

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			Early		
PSM_log_adj	95	11.22148	.2295933	9.578329	11.71901
age	95	18.40623	7.215394	12.24932	62.30137
elevator	95	.7473684	.4368266	0	1
story_nr	95	2.652632	1.464243	1	6
floor_area	95	82.74737	23.83809	42	143
rooms	95	3.031579	.6756027	2	5
bathrooms	95	1.157895	.3665767	1	2
wc	95	1.273684	.4482141	1	2
train_dist	95	.3398563	.1677461	.1612382	1.251396
less_250m	95	.1684211	.3762251	0	1
less_500m	95	.7578947	.4306302	0	1
less_1000m	95	.0631579	.2445372	0	1
less_1500m	95	.0105263	.1025978	0	1
over_1500m	95	0	0	0	0
border_water	95	.6421053	.4819241	0	1

Table A.2.11. Descriptive Statistics Ski Before

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			Before		
PSM_log_adj	217	11.16377	.1546576	10.23628	11.63478
age	217	11.57408	6.07853	7.205479	45.84932
elevator	217	.7880184	.4096569	0	1
story_nr	217	2.788018	1.361251	1	6
floor_area	217	80.81567	23.50341	42	168
rooms	217	3.235023	.748498	1	5
bathrooms	217	1.276498	.4483	1	2
wc	217	1.391705	.5598655	1	3
train_dist	217	.7910798	.3544492	.1612382	1.676635
less_250m	217	.0092166	.0957806	0	1
less_500m	217	.3133641	.4649335	0	1
less_1000m	217	.1382488	.345959	0	1
less_1500m	217	.5299539	.500256	0	1

over_1500m	217	.0092166	.0957806	0	1
border_water	217	.7327189	.4435635	0	1

Table A.2.12. Descriptive Statistics Ski During

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
			During		
PSM_log_adj	534	11.03623	.1757182	10.46316	11.54469
age	534	21.42116	18.17119	1.49863	74.2137
elevator	534	.4007491	.4905097	0	1
story_nr	534	2.455056	1.431632	1	8
floor_area	534	73.44195	25.1827	26	194
rooms	534	2.898876	.864713	1	6
bathrooms	534	1.134831	.3526691	1	3
wc	534	1.181648	.4274365	1	3
train_dist	534	.8671648	.3466785	.1612382	1.69423
less_250m	534	.011236	.1055014	0	1
less_500m	534	.2078652	.4061603	0	1
less_1000m	534	.3782772	.485412	0	1
less_1500m	534	.3951311	.4893372	0	1
over_1500m	534	.0074906	.0863046	0	1
border_water	534	.5468165	.4982702	0	1

A.3 Time Dummy Model

Lillestrøm Houses

Table A.3.1. Descriptive Statistics Lillestrøm Time Dummy

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	728	10.71532	.5885369	8.630411	12.63842
age	728	67.47972	28.22348	11.55068	120.1205
lot_area	728	648.5069	271.4756	126	4113
floor_area	728	165.2459	77.04784	28	473
rooms	728	4.502747	1.542606	1	13
bathrooms	728	1.245879	.5310026	1	5
wc	728	1.391484	.658692	1	5
train_dist	728	1.051047	.489545	.2188379	4.663333
less_250m	728	.0041209	.0641057	0	1
less_500m	728	.0659341	.2483374	0	1
less_1000m	728	.3942308	.4890208	0	1
less_1500m	728	.4752747	.4997316	0	1
over_1500m	728	.0604396	.2384633	0	1
border_water	728	.0068681	.0826459	0	1
stories	728	2.784341	.5924113	1	4
y_1991	728	.0274725	.1635681	0	1
y_1992	728	.0151099	.122074	0	1

y_1993	728	.0151099	.122074	0	1
y_1994	728	.0260989	.1595391	0	1
y_1995	728	.0233516	.1511215	0	1
y_1996	728	.032967	.1786731	0	1
y_1997	728	.0521978	.2225786	0	1
y_1998	728	.0467033	.2111477	0	1
y_1999	728	.0343407	.1822279	0	1
y_2000	728	.0549451	.2280296	0	1
y_2001	728	.0563187	.2306946	0	1
y_2002	728	.0425824	.2020526	0	1
y_2003	728	.0631868	.2434659	0	1
y_2004	728	.0549451	.2280296	0	1
y_2005	728	.0865385	.2813508	0	1
y_2006	728	.0728022	.2599902	0	1
y_2007	728	.092033	.2892712	0	1
y_2008	728	.0576923	.233321	0	1
y_2009	728	.0741758	.262237	0	1
y_2010	728	.0714286	.2577164	0	1

Lillestrøm Apartments

Table A.3.2. Descriptive Statistics Lillestrøm Time Dummy

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	365	11.15099	.3197919	9.671189	13.1675
age	365	27.50301	18.80436	12.11781	75.52055
elevator	365	.5041096	.5006694	0	1
story_nr	365	2.276712	1.191836	1	7
floor_area	365	76.41918	28.41224	20	278
rooms	365	2.989041	.9168091	1	6
bathrooms	365	1.068493	.252937	1	2
wc	365	1.2	.4073501	1	3
train_dist	365	.8274824	.2577816	.2461064	1.55318
less_250m	365	.0164384	.1273285	0	1
less_500m	365	.0684932	.252937	0	1
less_1000m	365	.5945205	.4916586	0	1
less_1500m	365	.3150685	.4651808	0	1
over_1500m	365	.0054795	.0739216	0	1
border_water	365	.5013699	.5006845	0	1
y_1991	365	.0027397	.0523424	0	1
y_1992	365	0	0	0	0
y_1993	365	.0082192	.0904103	0	1
y_1994	365	.0082192	.0904103	0	1
y_1995	365	.0054795	.0739216	0	1
y_1996	365	.0054795	.0739216	0	1
y_1997	365	.0273973	.1634621	0	1
y_1998	365	.0136986	.1163963	0	1

y_1999	365	.0109589	.1042525	0	1
y_2000	365	.0027397	.0523424	0	1
y_2001	365	.0273973	.1634621	0	1
y_2002	365	.0082192	.0904103	0	1
y_2003	365	.0246575	.155292	0	1
y_2004	365	.0191781	.1373389	0	1
y_2005	365	.0465753	.2110168	0	1
y_2006	365	.0712329	.2575665	0	1
y_2007	365	.0767123	.2664998	0	1
y_2008	365	.2383562	.4266629	0	1
y_2009	365	.1972603	.3984767	0	1
y_2010	365	.2054795	.4046062	0	1

Ski Houses

Table A.3.3. Descriptive Statistics Ski Time Dummy

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	1,171	10.61796	.4494505	7.611658	11.86611
age	1,171	36.20238	25.5342	.4246575	119.3315
lot_area	1,171	969.7451	1448.983	95	14669
floor_area	1,171	173.0786	64.10451	68	549
rooms	1,171	5.151153	1.261611	1	12
bathrooms	1,171	1.517506	.6367594	1	4
wc	1,171	1.890692	.7303017	1	5
train_dist	1,171	1.541974	1.498521	.2577406	7.821084
less_250m	1,171	0	0	0	0
less_500m	1,171	.0614859	.2403221	0	1
less_1000m	1,171	.2826644	.450487	0	1
less_1500m	1,171	.4321093	.4955811	0	1
over_1500m	1,171	.2237404	.4169281	0	1
border_water	1,171	.0350128	.1838907	0	1
stories	1,171	1.972673	.7674609	1	4
y_2000	1,171	.0153715	.1230777	0	1
y_2001	1,171	.0187874	.1358313	0	1
y_2002	1,171	.0170794	.1296228	0	1
y_2003	1,171	.0111016	.1048225	0	1
y_2004	1,171	.0128096	.1125002	0	1
y_2005	1,171	.0145175	.1196619	0	1
y_2006	1,171	.0162254	.1263955	0	1
y_2007	1,171	.0247652	.155475	0	1
y_2008	1,171	.0145175	.1196619	0	1
y_2009	1,171	.0196413	.1388237	0	1
y_2010	1,171	.0204953	.1417477	0	1
y_2011	1,171	.0204953	.1417477	0	1
y_2012	1,171	.0614859	.2403221	0	1
y_2013	1,171	.0333049	.1795081	0	1

y_2014	1,171	.0392827	.1943497	0	1
y_2015	1,171	.0367208	.1881557	0	1
y_2016	1,171	.0315969	.1749992	0	1
y_2017	1,171	.0674637	.2509305	0	1
y_2018	1,171	.0828352	.2757507	0	1
y_2019	1,171	.1562767	.3632726	0	1
y_2020	1,171	.1357814	.3427026	0	1
y_2021	1,171	.1289496	.3352874	0	1
y_2022	1,171	.0204953	.1417477	0	1

Ski Apartments

Table A.3.4. Descriptive Statistics Ski Time Dummy

VARIABLE	*OBS*	*MEAN*	*STD. DEV.*	*MIN*	*MAX*
PSM_log_adj	846	11.08975	.1913699	9.578329	11.71901
age	846	18.55682	15.53127	1.49863	74.2137
elevator	846	.5390071	.498771	0	1
story_nr	846	2.562648	1.423463	1	8
floor_area	846	76.37825	24.88979	26	194
rooms	846	2.995272	.8313254	1	6
bathrooms	846	1.173759	.3853185	1	3
wc	846	1.245863	.4752583	1	3
train_dist	846	.7884358	.3709396	.1612382	1.69423
less_250m	846	.0283688	.1661223	0	1
less_500m	846	.2966903	.457069	0	1
less_1000m	846	.2813239	.4499111	0	1
less_1500m	846	.3865248	.4872412	0	1
over_1500m	846	.0070922	.0839657	0	1
border_water	846	.6052009	.4890966	0	1
y_2000	846	.001182	.0343807	0	1
y_2001	846	.0047281	.0686392	0	1
y_2002	846	.0023641	.0485929	0	1
y_2003	846	.0094563	.0968397	0	1
y_2004	846	.0082742	.0906393	0	1
y_2005	846	.0023641	.0485929	0	1
y_2006	846	.0200946	.1404068	0	1
y_2007	846	.0177305	.1320482	0	1
y_2008	846	.0070922	.0839657	0	1
y_2009	846	.0378251	.1908858	0	1
y_2010	846	.0401891	.1965187	0	1
y_2011	846	.0141844	.1183205	0	1
y_2012	846	.0094563	.0968397	0	1
y_2013	846	.0460993	.2098242	0	1
y_2014	846	.0886525	.2844096	0	1
y_2015	846	.1205674	.3258165	0	1

y_2016	846	.0508274	.2197751	0	1
y_2017	846	.107565	.3100135	0	1
y_2018	846	.1052009	.3069937	0	1
y_2019	846	.0992908	.2992289	0	1
y_2020	846	.0768322	.2664825	0	1
y_2021	846	.1146572	.3187963	0	1
y_2022	846	.0141844	.1183205	0	1

Appendix B – Regression Results

Here we have included the remaining results from the carried analysis that is not presented in the main text. The following tables show the results from continuous distance measure. We decided to put these findings in the appendix, and have not discussed them in the thesis, as we found it to be redundant to our ring band models. In B.2 Time dummy we also included the regression result for the ring band models used to plot our figures.

B.1 Development Model

Table B.1.1. Before-during-after Lillestrøm Houses Continuous Distance

	BEFORE 1991-1994			*DURING 1995- Aug 1999*			*AFTER Aug 1999 -2010*		
PSM_log_a	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	-.00522	-1.72	0.091	.00272	1.60	0.113	.00099	1.69	0.091
lot_area	-.00021	-0.61	0.542	.00004	0.43	0.665	.00034	4.03	0.000
floor_area	-.00426	-4.57	0.000	-.00489	-5.53	0.000	-.00522	-17.85	0.000
rooms	-.02459	-0.44	0.665	-.13876	-3.28	0.001	-.04571	-3.14	0.002
bathrooms	-.15777	-0.56	0.580	.16638	1.29	0.201	-.0088	-0.17	0.863
wc	.07236	0.29	0.770	.08536	0.71	0.477	.12264	2.84	0.005
train_dist	-.04242	-0.27	0.792	.08149	0.69	0.489	-.17673	-5.57	0.000
border_wat	0			0			-.00294	-0.02	0.986
stories	-.22825	-1.99	0.052	.14143	1.77	0.079	.00829	0.31	0.760
_cons	12.6850	25.32	0.000	10.9843	34.25	0.000	11.55784	107.28	0.000
Adj. R^2	0.4757 (0.5456)			0.4978 (0.5299)			0.5625 (0.5698)		
N	61			126			541		

Note: The colors denote the significance level of 1%, 5% and 10%.

Table B.1.2. Before-during-after Lillestrøm Apartments Continuous Distance

	BEFORE 1991-1994			*DURING 1995-1999*			*AFTER 2000-2010*		
PSM_log_a	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age				.02494	1.62	0.127	-.00299	-3.21	0.001
elevator				.77971	1.59	0.134	.08475	2.49	0.013
story_nr				-.10226	-0.95	0.356	.04396	4.14	0.000
floor_area				-.00357	-0.24	0.811	-.00149	-1.36	0.173

rooms				-.04406	-0.15	0.880	-.07853	-2.77	0.006
bathrooms				.0079	0.01	0.989	.06247	0.93	0.354
wc				-.28845	-0.72	0.483	.18205	4.29	0.000
train_dist				-.25091	-0.76	0.461	-.18498	-2.55	0.011
border_wat				-.28233	-0.97	0.348	.03234	3.13	0.002
_cons				11.1957	18.1	0.000	11.2628	129.83	0.000
Adj. R^2	0			0.0562 (0.4255)			0.4403 (0.4553)		
N	7*			24			337		

Note: The colors denote the significance level of 1%, 5% and 10%. *This interval could not be regressed as there were only seven observations.

Table B.1.3. Early-Before-During Ski Houses Continuous Distance

	EARLY 2000 - 2009			*BEFORE January 2010 – June 2015*			*DURING June 2015 – March 2022*		
PSM_log_a	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00397	2.40	0.017	.00055	0.33	0.744	-.00073	-1.42	0.157
lot_area	.00004	0.68	0.498	.00001	0.49	0.623	-.00001	-1.47	0.141
floor_area	-.00455	-5.87	0.000	-.00361	-6.63	0.000	-.00343	-16.16	0.000
rooms	-.03635	-1.37	0.172	-.00075	-0.03	0.975	-.00427	-0.43	0.669
bathrooms	-.08853	-1.10	0.273	.08903	1.35	0.179	.03815	1.30	0.193
wc	.03152	0.42	0.672	-.11504	-1.74	0.083	-.01476	-0.68	0.494
train_dist	-.13207	-5.06	0.000	-.14557	-7.35	0.000	-.07023	-9.65	0.000
border_wat	.06891	0.27	0.785	.14147	0.91	0.363	.14362	2.30	0.022
stories	.00396	0.06	0.950	.02034	0.43	0.667	.0491	2.81	0.005
_cons	11.5328	61.7	0.000	11.4871	82.0	0.000	11.2853	196.62	0.000
Adj. R^2	0.3144 (0.3466)			0.4669 (0.4886)			0.4197 (0.4266)		
N	193			222			756		

Note: The colors denote the significance level of 1%, 5% and 10%.

Table B.1.4. Early-Before-During Ski Apartments Continuous Distance

	EARLY 2000 – 2009			*BEFORE January 2010 – June 2015*			*DURING June 2015 – March 2022*		
PSM_log_a	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00375	0.83	0.408	-.00634	-3.05	0.003	-.00275	-7.06	0.000
elevator	-.06852	-0.89	0.374	-.05427	-2.09	0.038	-.02309	-1.53	0.126
story_nr	.05934	2.37	0.020	.04037	5.46	0.000	.00816	1.84	0.067
floor_area	-.00092	-0.38	0.701	-.00125	-1.77	0.078	-.00442	-9.48	0.000
rooms	.02536	0.40	0.687	.0244	1.18	0.239	.00479	0.41	0.683
bathrooms	.08274	0.81	0.418	-.02068	-0.55	0.583	.0503	1.51	0.133
wc	-.05366	-0.54	0.593	.06928	2.17	0.031	.15836	5.46	0.000
train_dist	-.13998	-0.54	0.589	-.25169	-7.38	0.000	-.13373	-6.88	0.000
border_wat	.02821	0.39	0.700	.11508	3.80	0.000	.07744	5.89	0.000
_cons	11.0472	59.2 0	0.000	11.2342	150. 04	0.000	11.2244	326.31	0.000
Adj. R^2	0.0113 (0.1060)			0.3413 (0.3688)			0.3647 (0.3755)		
N	95			217			534		

Note: The colors denote the significance level of 1%, 5% and 10%.

B.2 Time Dummy Regressions

Table B.2.1. Time Dummy Model Lillestrøm Houses

	CONTINUOUS DISTANCE			*RING BANDS DISTANCE*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00147	2.66	0.008	.00161	2.88	0.004
lot_area	.00013	2.37	0.018	.00014	2.40	0.017
floor_area	-.00488	-17.56	0.000	-.00485	-17.37	0.000
rooms	-.07504	-5.48	0.000	-.07489	-5.44	0.000
bathrooms	.00545	0.11	0.910	.01508	0.31	0.756
wc	.12962	3.12	0.002	.12387	2.97	0.003
train_dist	-.14137	-4.55	0.000	-		
less_250m	-			.26376	1.08	0.281
less_500m	-			.34901	4.05	0.000
less_1000m	-			.2043	3.09	0.002
less_1500m	-			.25918	3.95	0.000
border_wat	.02958	0.16	0.872	.02426	0.13	0.895
stories	.01656	0.64	0.522	.03331	1.27	0.204
y_1991	-.26496	-2.59	0.010	-.29151	-2.82	0.005
y_1992	-.36011	-2.78	0.006	-.3646	-2.80	0.005
y_1993	.0500	0.39	0.699	.00124	0.01	0.992
y_1994	-.17906	-1.72	0.086	-.19865	-1.90	0.058
y_1995	-.24072	-2.23	0.026	-.22721	-2.10	0.036
y_1996	-.3728	-3.86	0.000	-.40306	-4.14	0.000
y_1997	-.15334	-1.88	0.060	-.17392	-2.12	0.034
y_1998	-.13808	-1.63	0.103	-.17193	-2.01	0.044
y_1999	-.06729	-0.72	0.474	-.09393	-1.00	0.320
y_2000	-.17993	-2.24	0.026	-.18312	-2.27	0.024
y_2001	.01589	0.20	0.842	.00785	0.10	0.922
y_2002	-.02696	-0.31	0.758	-.04085	-0.47	0.641
y_2003	-.06004	-0.78	0.437	-.07465	-0.96	0.335
y_2004	-.14202	-1.77	0.077	-.1632	-2.02	0.044
y_2006	.06524	0.89	0.376	.0417	0.56	0.574
y_2007	.13648	1.95	0.051	.10373	1.48	0.141
y_2008	.04766	0.60	0.549	.05117	0.63	0.527
y_2009	.13038	1.77	0.077	.09618	1.30	0.193
y_2010	.13131	1.76	0.078	.12897	1.73	0.085
_cons	11.6225	103.41	0.000	11.1963	92.09	0.000
Adj. R^2	0.5511 (0.5684)			0.5491 (0.5683)		
N	728			728		

Note: The colors denote the significance level of 1%, 5% and 10%.

Table B.2.2. Time Dummy Model Lillestrøm Apartments

	CONTINUOUS DISTANCE			*RING BANDS DISTANCE*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	-.00337	-3.41	0.001	-.0026	-2.67	0.008
elevator	.1001	2.89	0.004	.10521	3.02	0.003
story_nr	.04665	4.22	0.000	.0517	4.72	0.000
floor_area	-.00422	-4.08	0.000	-.00423	-4.11	0.000
rooms	-.0339	-1.20	0.230	-.0338	-1.20	0.232
bathrooms	.02397	0.36	0.716	.02441	0.38	0.707
wc	.22565	5.16	0.000	.21032	4.88	0.000
train_dist	-.19618	-2.70	0.007	-		
less_250m	-			-.00133	-0.01	0.995
less_500m	-			-.12748	-0.60	0.549
less_1000m	-			-.06912	-0.34	0.737
less_1500m	-			-.22791	-1.12	0.262

border_water	.08397	2.32	0.021	.09126	2.45	0.015
y_1991	.16907	0.72	0.473	.17616	0.75	0.452
y_1992	0			0		
y_1993	.79313	5.19	0.000	.72502	4.74	0.000
y_1994	-.19003	-1.32	0.188	-.28249	-1.94	0.054
y_1995	.15004	0.87	0.386	.01122	0.06	0.955
y_1996	.21141	1.24	0.215	.25597	1.53	0.128
y_1997	-.20094	-2.15	0.032	-.17077	-1.79	0.075
y_1998	-.19729	-1.73	0.084	-.20428	-1.76	0.080
y_1999	-.25603	-2.00	0.046	-.30699	-2.23	0.027
y_2000	.00204	0.01	0.993	-.10837	-0.46	0.643
y_2001	.10315	1.16	0.246	.04549	0.49	0.624
y_2002	.14282	1.01	0.313	.14257	1.00	0.318
y_2003	.31096	3.41	0.001	.31031	3.34	0.001
y_2004	-.06005	-0.58	0.561	-.09512	-0.90	0.370
y_2006	-.05459	-0.72	0.469	-.0794	-1.00	0.320
y_2007	.0202	0.31	0.758	.0057	0.08	0.935
y_2008	.08054	1.51	0.133	.03944	0.64	0.524
y_2009	.0584	1.08	0.281	.02404	0.38	0.702
y_2010	.02935	0.55	0.585	.00273	0.04	0.965
_cons	11.2919	122.96	0.000	11.2593	50.75	0.000
Adj. R^2	0.4881 (0.5260)			0.5032 (0.5442)		
N	365			365		

Note: The colors denote the significance level of 1%, 5% and 10%.

Table B.2.3. Time Dummy Model Ski Houses

	CONTINUOUS DISTANCE			*RING BANDS DISTANCE*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	.00004	0.08	0.932	-.00122	-2.32	0.021
lot_area	-5.75e-06	-0.74	0.456	-.000022	-2.71	0.007
floor_area	-.00363	-17.62	0.000	-.0037	-17.13	0.000
rooms	-.01803	-1.97	0.049	-.01729	-1.83	0.068
bathrooms	.02728	1.04	0.300	.00116	0.04	0.966
wc	-.00947	-0.43	0.664	.00651	0.29	0.774
train_dist	-.08819	-12.32	0.000	-		
less_250m	-			-		
less_500m	-			.04221	0.82	0.410
less_1000m	-			.2569	8.24	0.000
less_1500m	-			.16742	5.79	0.000
border_water	.12928	2.09	0.037	.20406	3.10	0.002
stories	.0540	3.15	0.002	.06173	3.46	0.001
y_2000	-.29304	-2.70	0.007	-.30303	-2.70	0.007
y_2001	-.14797	-1.43	0.152	-.15331	-1.44	0.151
y_2002	.07192	0.68	0.498	.03576	0.33	0.745
y_2003	-.1147	-0.96	0.339	-.1183	-0.95	0.340
y_2004	-.02219	-0.19	0.846	-.03798	-0.32	0.749
y_2005	-.08917	-0.80	0.423	-.04668	-0.40	0.686
y_2006	-.01536	-0.14	0.886	-.0338	-0.30	0.761
y_2007	-.05159	-0.54	0.592	-.09461	-0.95	0.343
y_2008	.07262	0.66	0.511	.08614	0.75	0.451
y_2009	.00494	0.05	0.961	-.0353	-0.34	0.737
y_2010	.15948	1.59	0.113	.11368	1.10	0.274
y_2012	.15247	1.36	0.175	.11617	1.85	0.065
y_2013	.13403	1.48	0.138	.12436	1.33	0.183
y_2014	.00667	0.08	0.939	-.00185	-0.02	0.984
y_2015	.09704	1.10	0.273	.08031	0.88	0.381
y_2016	.01366	0.15	0.881	.00138	0.01	0.988
y_2017	.08829	1.08	0.281	.0536	0.63	0.527

y_2018	.11452	1.43	0.153	.09888	1.19	0.233
y_2019	.16427	2.17	0.031	.16172	2.05	0.041
y_2020	.16389	2.14	0.032	.15325	1.94	0.053
y_2021	.13094	1.70	0.090	.11831	1.48	0.138
_cons	11.2506	126.52	0.000	11.0416	115.55	0.000
Adj. R^2	0.4054 (0.4211)			0.3663 (0.3842)		
N	1,171			1,171		

Note: The colors denote the significance level of 1%, 5% and 10%.

Table B.2.4. Time Dummy Model Ski Apartments

	CONTINUOUS DISTANCE			*RING BANDS DISTANCE*		
PSM_log_adj	*Coefficient*	*t*	*P>t*	*Coefficient*	*t*	*P>t*
age	-.00253	-5.92	0.000	-.00231	-5.17	0.000
elevator	-.01094	-0.79	0.432	.02223	1.43	0.152
story_nr	.01928	4.80	0.000	.01716	4.22	0.000
floor_area	-.00341	-8.32	0.000	-.00315	-7.62	0.000
rooms	-.00024	-0.02	0.982	-.00062	-0.06	0.954
bathrooms	.03777	1.49	0.138	.01877	0.73	0.467
wc	.1302	5.83	0.000	.12812	5.71	0.000
train_dist	-.12427	-6.79	0.000	-		
less_250m	-			.37485	4.83	0.000
less_500m	-			.23437	3.63	0.000
less_1000m	-			.26934	4.23	0.000
less_1500m	-			.20875	3.26	0.001
border_water	.07027	5.48	0.000	.0505	3.83	0.000
y_2000	.13742	0.91	0.365	.1307	0.86	0.391
y_2001	.3029	3.89	0.000	.35073	4.45	0.000
y_2002	.04047	0.37	0.709	.09055	0.83	0.407
y_2003	.14251	2.49	0.013	.08446	1.20	0.231
y_2004	.16175	2.69	0.007	.12712	1.90	0.058
y_2005	.14087	1.30	0.194	.22362	2.04	0.041
y_2006	.07889	1.92	0.056	.14398	3.43	0.001
y_2007	-.05529	-1.28	0.201	.00067	0.02	0.988
y_2008	.17439	2.73	0.007	.18831	2.92	0.004
y_2009	.11351	3.50	0.000	.16579	4.97	0.000
y_2010	.11649	3.65	0.000	.15998	4.91	0.000
y_2011	.11005	2.32	0.020	.16715	3.46	0.001
y_2012	.00822	0.15	0.885	.04072	0.72	0.475
y_2013	.12382	4.30	0.000	.1473	5.06	0.000
y_2014	-.00268	-0.12	0.907	.01227	0.52	0.602
y_2016	-.02209	-0.80	0.425	-.00949	-0.34	0.736
y_2017	-.03994	-1.66	0.098	-.05329	-2.20	0.028
y_2018	.00499	0.21	0.831	.01519	0.64	0.519
y_2019	-.0150	-0.64	0.525	-.00826	-0.34	0.730
y_2020	-.02691	-1.03	0.301	-.0212	-0.81	0.420
y_2021	-.06460	-2.78	0.006	-.0533	-2.26	0.024
_cons	11.1973	299.68	0.000	10.8525	156.04	0.000
Adj. R^2	0.3860 (0.4085)			0.3803 (0.4052)		
N	846			846		

Note: The colors denote the significance level of 1%, 5% and 10%.