The anticipation effect of a light rail transit line on housing prices in the Helsinki region*

Eetu Kauria
Department of Economics, University of Turku
eekaur@utu.fi

Abstract

I analyze how housing markets in Espoo and Helsinki anticipate the construction of a new light rail transit connection called Jokeri Light Rail. I use geocoded micro-level housing transaction data from 2003–2019. As an econometric identification strategy, I utilize difference-in-differences estimation with a hedonic price model. My main result is that, on average, apartment prices increase by 5 percent more within 800 meters of the Jokeri Light Rail stops than apartments farther away. A rough estimate of the total windfall for homeowners indicates that the anticipated benefits exceed the cost estimate for the investment five to eight years before the Jokeri Light Rail becomes operational.

Keywords: *anticipation effect, difference-in-differences, housing market, light rail transit*
JEL codes: *D61, R41*

**I am grateful to Janne Tukiainen, Oskari Harjunen, Elias Oikarinen, Tuukka Saarimaa, two anonymous referees, and Editor Mika Kortelainen for their helpful comments along the way.*

1. Introduction

Public services significantly impact citizens' well-being and satisfaction in a particular neighborhood (James 2009). As public investments enhance a neighborhood's service level, the willingness to pay (WTP) for housing near the investment should increase. This leads to higher demand for land and housing near the investment (Alonso 1964; Muth 1969). Consequently, housing prices grow depending on the elasticity of supply for housing. For the policy-makers, whose interest should be to maximize their respective citizens' utility within a limited budget, it is crucial to assess the costs and benefits of various public investment projects and only execute the most effective ones.

In this paper, I assess the impact of a light rail transit (LRT) investment on housing prices. Specifically, I consider the price changes to reflect the desirability of an area. *Ergo*, I deem the changes in monetary values to be an indicator of the public's willingness to pay for the rail investment (see Gibbons and Machin 2005).

This study investigates how housing markets in Espoo and Helsinki react to the decision to build Jokeri Light Rail, a rail line running 25 kilometers from Keilaniemi in the west to Itäkeskus in the east. To my knowledge, this is the first study concerning the subject. To identify the price responses to Jokeri Ligh Rail, I employ rich housing transaction data and combine a difference-in-differences identification strategy with a hedonic price model[1]. My main result shows that the prices of apartments near the investment increase by 5 percent more than apartments farther away.

Moreover, I provide a cost-benefit analysis (CBA) of the rail investment, where I utilize the housing market effect as an indicator of the investment's benefits (see Weisbrod et al. 2016). The CBA of this paper is the first assessment of Jokeri Light Rail that accounts for the overall benefits of the investment so far as I am aware. An earlier CBA, which did not consider the impact on the housing market but rather only on traffic, emissions and accident rate, found the investment's costs to surpass its benefits (Project assessment of Jokeri Light Rail 2019).

I do not explicitly analyze the specific channels through which the rail investment impacts the housing market. For example, the expected urban development might affect the properties more than the initial accessibility improvements. In addition, a rail investment can affect other markets as well, including the labor market. The construction phase of the investment may also cause traffic frictions (see Lewis and Bajari 2011). However, if the housing markets are efficient, all the costs and benefits from a rail investment are reflected in dwelling prices (Gibbons and Machin 2005).

The impact of rail investment is a rather complex problem to analyze. The identification strategy in previous studies varies: some rely merely on the association between the investment and housing prices based on hedonic models, which gives ambiguous results at best, while others build upon more reliable quasi-experimental approaches. Consequently, the studies' results vary significantly (Debrezion et al. 2007; Mohammad et al. 2013). While most studies find a positive relationship between investment and housing prices, some observe adverse or ambiguous effects.

Examples of recent studies using a quasi-experimental research design include Zhou et al. (2019), who find a 3.8 percent price premium when a new metro line opened in Shanghai, and Fesselmeyer and Liu (2018), who study a metro expansion in Singapore and observe a 1.8 percent price increase in apartments within 500 meters of the existing stations.

However, while Ke and Gkritza (2019) find an announcement of a new LRT investment to affect property values positively in Charlotte-Mecklenburg, North Carolina, they find a negative effect during the operations phase. Camins-Esakov and Vandegrift (2018) analyze repeat sales in Bayonne, New Jersey, and detect no significant impact on dwelling prices after the construction of an LRT extension. Analogous to Zhou et al. (2019) and Ke and Gkritza (2019), this paper investigates the anticipation effect of a new LRT line with a quasi-experimental research design.

[1] *Several attributes affect a property's value, but these attributes cannot be purchased separately. Nonetheless, the values can be determined using a hedonic price model. (Rosen 1974; Kain and Quigley 1975.)*

Some modern studies use a state-of-the-art approach, combining a quasi-experimental design with cell phone ping data. Gupta et al. (2020) utilize this technique to assess a metro extension's anticipation effect in New York City. They find a 10 percent price increase in property values, which they credit to reduced commuter times and higher rents.

Research regarding the Finnish housing market is the most relevant to this paper as the housing markets react differently to external shocks, partly due to differences in market structures and the share of wealth used in housing (European Commission 2017). Unfortunately, there are very few studies concerning the impact of public transit investments in Finland employing a quasi-experimental approach, and even those examine only the impact of the metro.

Harjunen (2018) studies how building the West Metro in Espoo and Helsinki impacts dwelling prices. Using a quasi-experimental strategy, he finds a positive effect within 800 meters of the stations, even five years before the operations start. He compares price trends near the West Metro's stations to those near existing railway stations. The dwelling prices within the West Metro's buffer zones experience a 4 percent price increase. In addition, Laakso (1992) finds a positive impact from the Helsinki metro using a hedonic model. The identification strategy used in this paper is similar to the one used by Harjunen (2018), albeit here I examine the impact of Jokeri Light Rail instead of the West Metro.

2. Institutional setting

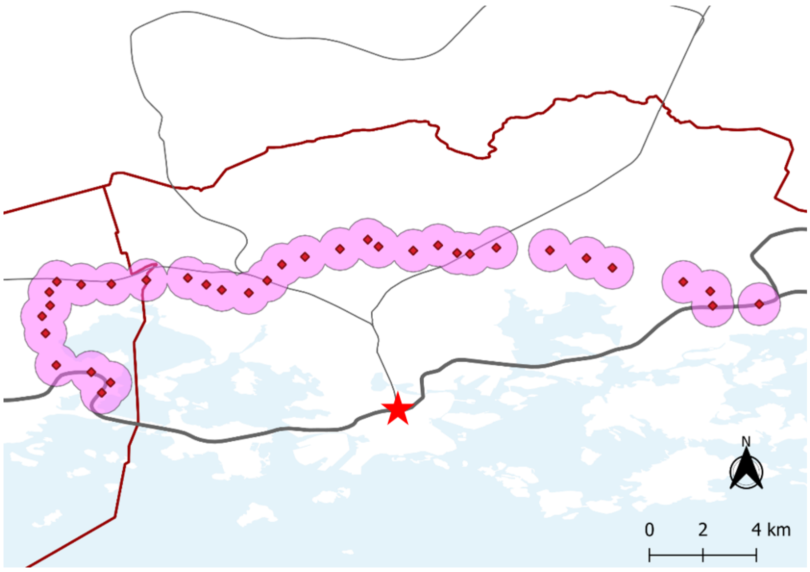
Helsinki is by far the most populous city in Finland: in 2019, it had 648,000 inhabitants, whereas the surrounding Helsinki region had over 1.49 million. These figures are expected to reach 820,000 and 1.92, respectively, by 2050. (Vuori and Kaasila 2019.) Accordingly, housing prices have increased more rapidly in Helsinki than in the rest of the country, and the trend is predicted to continue in the years to come (Laakso and Loikkanen 2016). In the Helsinki region, land values rise exponentially when travel time to the CBD (central business district) is reduced (Laakso and Loikkanen 2013).

Finland's urban rail network consists of tramways in southern Helsinki, a single metro line running from southern Espoo to eastern Helsinki, and commuter trains in the Helsinki region. Moreover, a tramway line is under construction in Tampere. Crosstown public transport in the Helsinki region is limited as only bus lines are in operation. The busiest bus line of the whole region is a crosstown connection named trunk route 550 (Jokeri Light Rail: Information). The trunk route 550 started its operations in August 2003.

The daily ridership of route 550 is already at its upper limit, with 40,000 daily passengers, and this figure is expected to double in the next ten years. Therefore the cities of Espoo and Helsinki have decided to construct a new crosstown LRT line called Jokeri Light Rail to ease the traffic congestion in this growing region. The travel time of Jokeri Light Rail will be identical to the current bus line, but the LRT will be more immune to congestion, and its capacity will be two to three times higher. (Jokeri Light Rail: Information.) Similar rail investments are being planned in other cities, such as in Vantaa (City of Vantaa 2019).

The route of Jokeri Light Rail will run from Keilaniemi in the west to Itäkeskus in the east. The Jokeri Light Rail will have 34 new stops along its 25-kilometer route, of which nine are in Espoo, and sixteen are in Helsinki. A substantial amount of residential housing is planned to be built along its route on top of workplaces for at least 20,000 people. (Jokeri Light Rail: Information.) Figure 1 shows the route of Jokeri Light Rail and 800-meter buffer zones around the stops.

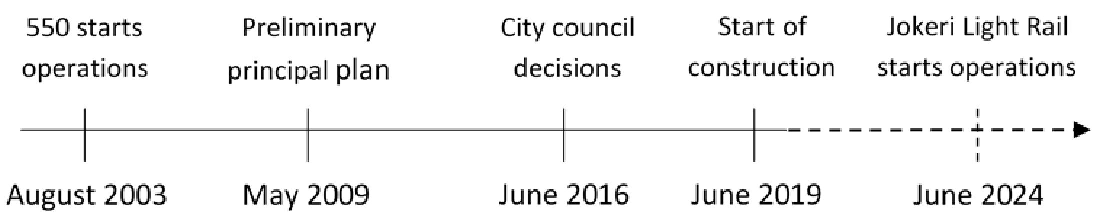
Figure 1: *The route of Jokeri Light Rail and the 800-meter buffer zones*



Note. The red star indicates the CBD (Helsinki Central railway station). The metro line is denoted by the dark grey line, railway lines with light grey, and municipality borders with dark red (General Guide Map of the City of Helsinki). The reference system is WGS 84.

The preliminary principal plan of Jokeri Light Rail was completed in May 2009 (Jokeri Light Rail 2009), while the project plan was completed in January 2016 (Jokeri Light Rail 2016a). The city councils of Espoo and Helsinki approved the project plan in June 2016 (Jokeri Light Rail 2016b). Construction began in June 2019, and the planned beginning of operations is June 2024 (Jokeri Light Rail: Construction). The project's final cost estimate was 386 million euros in 2019 (Jokeri Light Rail 2019). I present the timeline of the Jokeri Light Rail in Figure 2.

Figure 2: *The timeline of Jokeri Light Rail*



3. Methodology

3.1 Timing of the capitalization

In this paper, I analyze how Jokeri Light Rail capitalizes in property prices. Hence, I assess possible capitalization times by considering two different factors. Firstly, as in many previous studies about the housing market capitalization of an investment, I examine the dates of important political decisions. As discussed in the previous section, the most vital steps for Jokeri Light Rail took place in 2009, 2016, and 2019. However, information about the councils' decisions, for instance, might not immediately reach the public's awareness.

Secondly, I consider the information the public received about the investment to be of significant importance because capitalization is observed in the public's housing transactions. I view Google search figures between 2006 and 2019 as a proxy indicator of the public's information. These figures are presented in Table 1. The second column shows how the relative number of searches per year progresses, where a higher number means more searches. The third column displays

Table 1: *Public's information about Jokeri Light Rail between 2006 and 2019*

Year	Google search index	Number of weeks searched	Increase in number of weeks searched
2006	359	4	–
2007	476	5	25%
2008	743	11	120%
2009	748	13	18%
2010	809	10	-23%
2011	1,354	18	80%
2012	1,462	25	39%
2013	1,885	34	36%
2014	2,089	33	-3%
2015	2,433	48	45%
2016	1,329	69	44%
2017	2,695	75	9%
2018	3,495	77	3%
2019	4,135	90	17%

Note. Search words (in Finnish) "Raide-Jokeri" (term) and "Raide-Jokeri" (subject) inspected in Google Trends (2020). Inspected search weeks per year total 104. Google search index displays how the relative number of searches varies over time, higher meaning that more searches have been conducted. The number of weeks searched shows how many weeks (out of 104) the search words have been used on Google search.

the number of weeks in a year on which the search terms have been used (out of 104), and the fourth column shows the relative increase in the number of weeks searched.

Although there is an upward trend during the whole interval from 2006 to 2019, there are noticeable hikes in 2008, 2011, 2015–2016, and 2019. Subsequently, I regard 2012, 2016, and 2019 as the most likely moments of capitalization. However, to mitigate the risk of using an incorrect year for capitalization, I also estimate yearly effects.

3.2 Research design

I study the effects of the rail investment on the housing market using the investment decision as a quasi-experiment (see Billings 2011; Dubé et al. 2018). The aim is to measure the counterfactual price growth, i.e., how the property prices within the catchment areas of the upcoming Jokeri Light Rail stops would have developed had the investment not been made, and then compare that to the factual price development in the catchment areas.

I estimate the magnitude, timing, and geographical extent of the effect. Furthermore, I use this estimate to assess the value of the total windfall for homeowners. As the start of operations is still yet to come, I estimate the investment's anticipation effect (McDonald and Osuji 1995; Gibbons and Machin 2005).

Hedonic price models are widely used when assessing a rail investment's impact on the housing market. However, as hedonic models do not specify the effect's timing and often suffer from an omitted variable bias, the results cannot be interpreted as causal. (Parmeter and Pope 2013; Mohammad et al. 2017.)

In this paper, my identification strategy is a difference-in-differences (DID). It is one of the most used methods when evaluating the efficacy of policies (Ashenfelter and Card 1984; Billings 2011). In addition, I combine DID with a hedonic price model to achieve more reliable and precise results: the additional control variables should reduce the residual variance (see Papon et al. 2015).

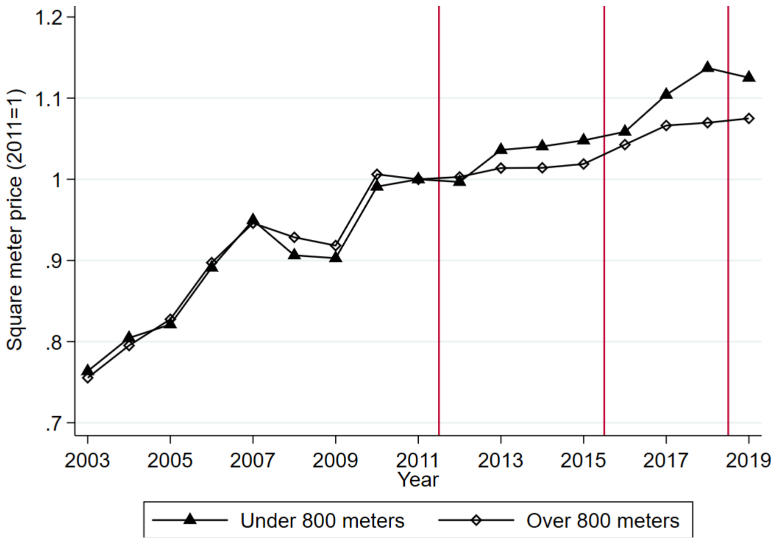
Using a DID model, three assumptions must be satisfied for the results to be interpreted causally: no spillovers between the treatment and the control group, parallel trends in the absence of treatment in both groups, and no coinciding policy reforms or other events that would affect the groups differently.

My primary treatment group comprises observations within 800 meters of the Jokeri Light Rail stops. In contrast, my primary control group includes observations outside these buffer zones but within certain postal code areas around the investment (see Table A1 in Appendix A). Moreover, I assume there are no spillovers between the treatment group and the control group because the dwellings are static, and I consider the impact of the treatment to lessen evenly as the distance to the stops increases.

I consider 800 meters to be the limit of an easily walkable distance (see Olszewski and Wibowo 2005; Harjunen 2018). Later, I proceed to show results for 200-meter bands, which support the usage of the 800-meter limit. Apart from the treatment-control group setting, I also test models using a continuous variable for distances measured in a hundred meters.

To test the assumption of parallel trends, I apply a graphical approach. I inspect the average yearly square meter price trends in Figure 3, both for the observations within the 800-meter buffer zones and the observations outside of these zones. The vertical lines represent possible capitalization times; see the discussion in Section 3.1. The year 2011 is indexed as 1.

Figure 3: *Square meter price trends for the treatment and control group*



Note. The vertical lines represent possible moments of capitalization (see Section 3.1). The year 2011 is indexed as one.

The square meter price trends are similar in both groups until 2012. There is a slight jump in the prices closer to the stops in 2013, which might be due to the increased awareness about Jokeri Light Rail. Nonetheless, according to Figure 3, the assumption of parallel trends holds well until 2012, after which the prices increase somewhat more within the 800-meter buffer zones. Another point of divergence in prices is noticeable after 2016.

Therefore, I consider the assumptions of parallel trends and no spillovers to be satisfied. Moreover, as I estimate the aggregate impact on housing prices along a circular route, there are most likely no coinciding events that would affect only the dwellings near the investment.

This study's econometric identification strategy (DID) estimates how the closeness to Jokeri Light Rail stops affects the dwelling prices. However, that does not necessarily reflect the accessibility changes. On the one hand, the estimates cannot explicitly take into account possible changes in housing supply[2], which can lead to downward skewed estimates; on the other hand, the investment might also shift the demand from the control to the treatment area, lowering the demand in the former, thus causing the estimates to be skewed upward. Finally, also the possible externalities are omitted from the explicit analysis.

3.3 Econometric models

I estimate four different econometric models, of which the initial ones are simple. Then, I test the robustness of these models by adding more control variables. The models differ from one another by interaction terms generated by combining time and distance variables. In addition to using two different types of measures for the distance to the stops, i.e., under and over 800 meters and a continuous variable, I use two variables for time: a before-and-after set-up, where the after-period begins in 2016 (see Section 3.1), and a year-wise set-up.

[2] *This may be negligible because an increase in housing supply presumably affects both the control and the treatment group similarly if the distance to the new housing is constant. Moreover, dwellings near the investments can be considered relatively reliable substitutes for each other.*

Model (1) is a clean DID model containing a before-and-after setting and the two distance groups; model (2) is a modification of the former where a continuous variable replaces the distance groups to estimate the intensity (i.e., gradient) of the treatment. In model (3), I measure time year-wise and distance in two groups. Again, I substitute the continuous variable for the distance groups in model (4). In model (1), represented by Equation (1), the price of an apartment i in year *t* is expressed as follows:

$$ln(SquareMeterPrice_{it}) = \alpha + \beta * JokeriLightRail_i + \gamma * After_t + \tau * (JokeriLightRail_i * After_t) + \delta * X_{it} + \varepsilon_{it} \quad (1)$$

, where the interaction term between the distance to Jokeri Light Rail and the time variable indicates the average treatment effect of the investment. X_{it} is a vector of a set of apartment characteristics used as controls, and ε_{it} are the error terms. Equations for models (3) and (4) are similar to (1), but I estimate yearly effects instead, *ergo* $After_t$ is replaced with $Year_t$.

As primary control variables, I include several housing and neighborhood characteristics (refer to Table 2). As an alternative control, in models with a discrete distance variable, I add postal code (of which there are 62) fixed effects to refine the models by capturing variation in small city district characteristics. When measuring the distance to the stops continuously, I use LRT stop (34) fixed effects, where I assign each observation to its closest Jokeri Light Rail stop. Likewise, standard errors are clustered by the postal code or LRT stop level, respectively. However, because the number of stops is relatively low, I also test the statistical significance based on the cluster generalization of the wild bootstrap in models 2 and 4 (see Cameron et al. 2008).

4. Data

The housing transaction data used in this study is obtained from the database of the Central Federation of Finnish Real Estate Agencies. These data include around 75% of the housing transactions in Finland conducted in the secondary markets (Central Federation of Finnish Real Estate Agencies: Housing markets). The data is very rich, including several micro-level variables about the transactions.

In this study, I include housing transactions made in 2003–2019 in 62 postal code areas along the route of Jokeri Light Rail (see Table A1 in Appendix A). I have geocoded[3] the transactions and calculated Euclidean distances between apartments and the nearest Jokeri Light Rail stop. This study only includes old apartment buildings, low-rise apartment buildings, maisonettes, rowhouses, and duplex houses. I exclude new[4] apartments and single-family houses because those may differ substantially from the other types of buildings.

Moreover, I have omitted observations that contained clear errors, e.g., if the geocoding was not successful on the street level. Observations with square meter prices outside three standard deviations from the mean are omitted because I consider them outliers (e.g., their characteristics might deviate considerably from the rest of the observations) or possible errors. The total number of observations shrinks slightly, from 78,999 to 77,378.

In Table 2, I present descriptive statistics over the housing transactions in Espoo and Helsinki in 2003–2019. Observations within the 800-meter buffer zones are used as a primary treatment group, whereas observations farther than 800 meters away from the Jokeri Light Rail stops are treated as a primary control group. Section 3.2 presents the discussion on the choice of the treatment and the control group.

---

[3] *Forward geocoding conducted in Stata using command opencagegeo and open data sources.*

[4] *Here, a new apartment refers to a newly constructed apartment, whereas old apartments are sold in secondary markets.*

The second column includes all the observations, while the third and fourth columns include only observations within the catchment areas. The fifth and sixth columns contain observations outside the 800-meter buffer zones. I have deflated all prices to the 2019 level using the CPI (Consumer Price Index 2020).

Table 2: *Descriptive statistics about housing transactions in Espoo and Helsinki in 2003–2019*

	All observations	**Under 800 meters**		**Over 800 meters**	
		2003–2015	**2016–2019**	**2003–2015**	**2016–2019**
N	77,378	16,419	5,192	41,983	13,784
Selling price	218,510 (111,494)	193,548 (92,452)	233,832 (98,528)	216,011 (113,972)	250,084 (120,567)
Price per square meter	3,578 (1,016)	3,420 (806)	4,041 (1,057)	3,466 (974)	3,931 (1,199)
Floor area (m²)	64.9 (29.6)	60.3 (28.6)	64.3 (28.5)	65.6 (30.1)	68.9 (29.2)
Apartment age (years)	38.9 (17.8)	39.5 (16.0)	43.5 (18.9)	37.4 (17.5)	41.2 (19.5)
Maintenance charge (€/m²)	3.76 (1.31)	3.59 (1.14)	4.20 (1.13)	3.65 (1.37)	4.15 (1.30)
Distance to nearest stop (m)	1,666 (1,043)	449 (201)	444 (198)	2,138 (836)	2,137 (827)
Travel time to CBD (min)	33.6 (7.8)	33.1 (5.0)	33.5 (5.1)	33.5 (8.7)	34.2 (8.5)
Freehold site (%)	62	62	58	63	60
Apartment building (%)	81	89	87	79	77
Condition (%)					
- *New or excellent*	1	0	3	0	3
- *Good*	53	49	58	52	59
- *Satisfactory*	37	40	35	36	34
- *Poor*	4	5	3	4	3
- *Unknown*	6	7	1	8	2

Note. Distances are measured to the nearest Jokeri Light Rail stop in a direct straight line. All prices are in euros and deflated to the 2019 level using the consumer price index. Travel time measured in minutes to Helsinki central railway station (CBD) using public transport during the rush hour, taking into account changes and waiting times. Figures are averages, standard errors are reported in parentheses. Travel times are from Tenkanen et al. (2018), other variables taken from the Central Federation of Finnish Real Estate Agencies.

Table 2 shows the number of observations in the control group to be double that of the number of observations in the treatment group. Nonetheless, most variable means in both distance groups are relatively similar, though there is some variation. However, the average square meter prices show more of an increase inside the catchment areas than outside them. The yearly number of observations is comparatively stable in both groups throughout the period, as illustrated in Figure A1 in Appendix A.

In my analysis, I only include those housing characteristics presented in Table 2, even though the data set contains several more. This choice stems from two reasons: firstly, most of the observations have no record of all the variables, and secondly, my models are relatively robust to the rest of the excluded characteristics. I consider travel time (to the CBD using public transport) as a proxy variable for local retail services and regional hubs. It is a static variable measured before the construction of Jokeri Light Rail begun.

5. Results

In this section, I present results from models 1–4. Moreover, I test the robustness of the results. For models 1 and 2, where the after-period begins from 2016, I show the estimates in table form. In models 1 and 2, I omit the observations between 2013 and 2015 to minimize the risk of contaminating the pre-treatment period as the price trends are dissimilar during those years (see Figure 3). When estimating yearly effects in models 3 and 4, I adopt a graphical presentation.

Extensive results for all models can be found in Appendix B. For my analysis, the most intriguing estimates are the interaction terms between the closeness to the Jokeri Light Rail stops, measured group-wise or continuously, and time measured in two groups or yearly. I treat these interactions as measures of how the apartments' square meter prices are affected by the investment.

5.1 Models 1 and 2

The results for models 1a–d are shown in Table 3. The second column (1a) includes only a fully saturated interaction term; the third column (1b) also includes postal code fixed effects, whereas, in the fourth (1c), I control (1a) by adding apartment characteristics as control variables. The fifth column (1d) combines all the former models. The reference group is observations farther than 800 meters from Jokeri Light Rail stops before 2016. Observations between 2013 and 2015 are omitted.

As Figure 3 already suggests, Jokeri Light Rail is estimated to positively impact dwelling prices within the catchment areas. According to model 1d, prices are 4.6 percent higher after 2016 within the 800-meter buffer zones than farther away. The estimate is robust for different housing and neighborhood characteristics used as additional controls. Moreover, the statistical significance of the estimate is at the 5 percent level.

I present the results for models 2a–d in Table 4. Here I measure the distance to the stops with a continuous variable. The second column (2a) includes only the interaction term, the third column (2b) also the LRT (i.e., Jokeri Light Rail) stop fixed effects. In the fourth column (2c), I control the initial model with apartment characteristics. All the former is com-

Table 3: *Model 1. Housing market effect in two distance groups before and after 2016*

Response variable: ln(price per square meter)	**Reference group: over 800 meters and before 2016**			
	(1a)	**(1b)**	**(1c)**	**(1d)**
Under 800 m*After	0.0486* (0.0252)	0.0502* (0.0265)	0.0342* (0.0179)	0.0456** (0.0205)
Under 800 m	-0.00977 (0.0516)	0.00277 (0.0164)	0.00689 (0.0263)	-0.0181 (0.0113)
After	0.139*** (0.0158)	0.144*** (0.0173)	0.117*** (0.0144)	0.139*** (0.0128)
Control variables	No	No	Yes	Yes
Postal code FE	No	Yes	No	Yes
N	63,745	63,745	63,745	63,745
R^2	0.061	0.061	0.476	0.316

*Note. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. Before-period is 2003–2012, after-period is 2016–2019. Observations from 2013–2015 are not used. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the postal code level (62) are reported in parentheses.*

Table 4: *Model 2. Housing market effect with continuous distance before and after 2016*

Response variable: ln(price per square meter)	**Reference group: before 2016**			
	(2a)	**(2b)**	**(2c)**	**(2d)**
Distance*After	-0.00309*** (0.000689)	-0.00269** (0.00107)	-0.00157** (0.000727)	-0.00207** (0.000888)
Distance	0.00172 (0.00299)	0.00200 (0.00173)	-0.00150 (0.00117)	-0.000368 (0.00108)
After	0.204*** (0.0172)	0.205*** (0.0193)	0.152*** (0.0149)	0.179*** (0.0150)
Control variables	No	No	Yes	Yes
LRT stop FE	No	Yes	No	Yes
N	63,745	63,745	63,745	63,745
R^2	0.063	0.063	0.480	0.409

*Note. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. Before-period is 2003–2012, after- period is 2016–2019. Observations from 2013–2015 are not used. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the LRT stop level (34) are reported in parentheses.*

bined in the fifth column (2d). The reference group is observations before 2016. Observations between 2013 and 2015 are omitted.

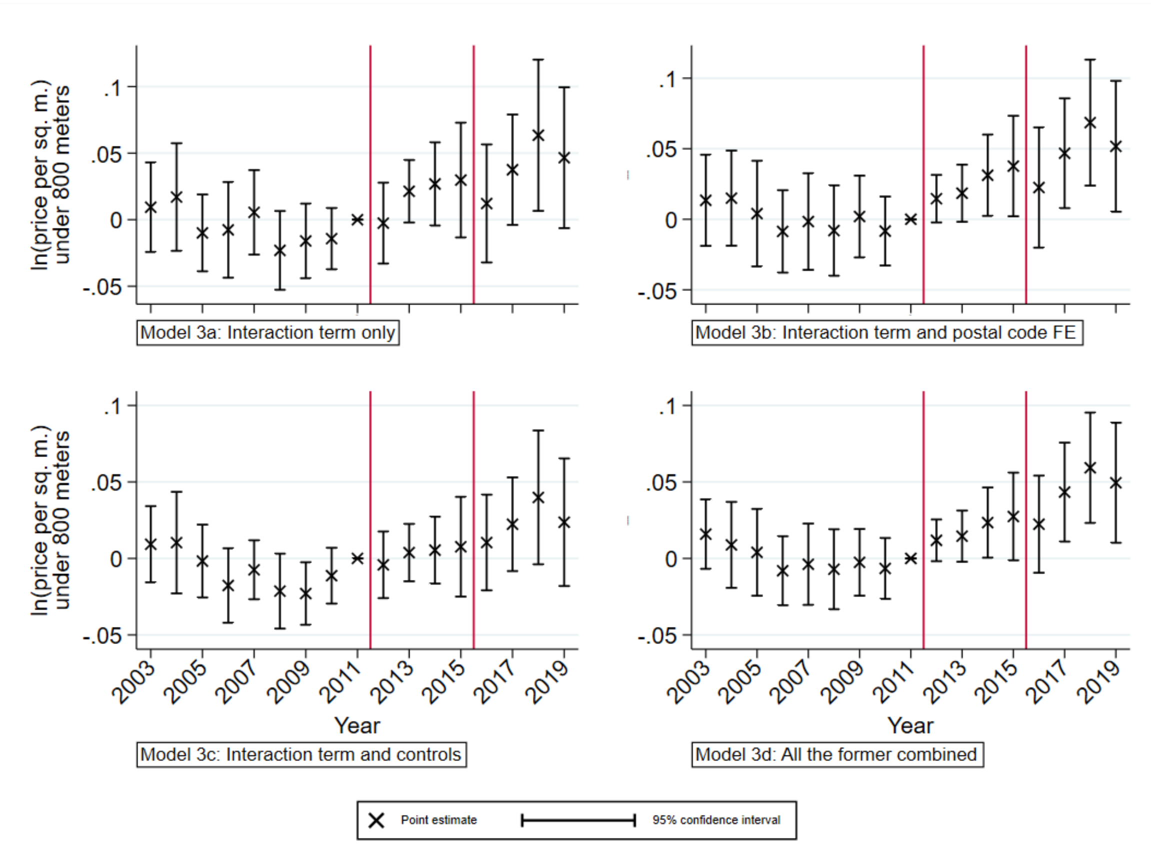
When the distance to the Jokeri Light Rail stops is measured with a continuous variable, the estimate for the investment's impact has a negative sign in every model, meaning that the closer the dwelling is to the stops, the higher the prices are after 2016. Model 2d shows that each hundred-meter increase in distance to the stops decreases prices by 0.2 percent after 2016. This estimate is significant at the 5 percent level. The wild bootstrap test produces comparable results (see Table B2 in Appendix B).

The control variables in models 1 and 2 impact the prices similarly. Travel time, the condition (lower value equals better condition), and floor area of the apartment correlate negatively with the prices; a freehold site and the scarcity of neighbors, on the other hand, correlate positively. The impact of age is non-linear. The maintenance charge does not have a significant effect on the prices.

5.2 Models 3 and 4

Figure 4 provides the interaction terms and their 95 percent confidence intervals for models 3a–d, where I estimate yearly effects with two distance groups. Model 3a includes only the fully saturated interaction term. Model 3b contains the interaction term and postal code fixed effects, whereas model 3c includes housing and neighborhood characteristics but no fixed effects. Finally, model 3d combines all the former. The reference group is observations outside the 800-meter buffer zones and in 2011.

Figure 4: *Models 3a–d. The yearly impact of Jokeri Light Rail in two distance groups*



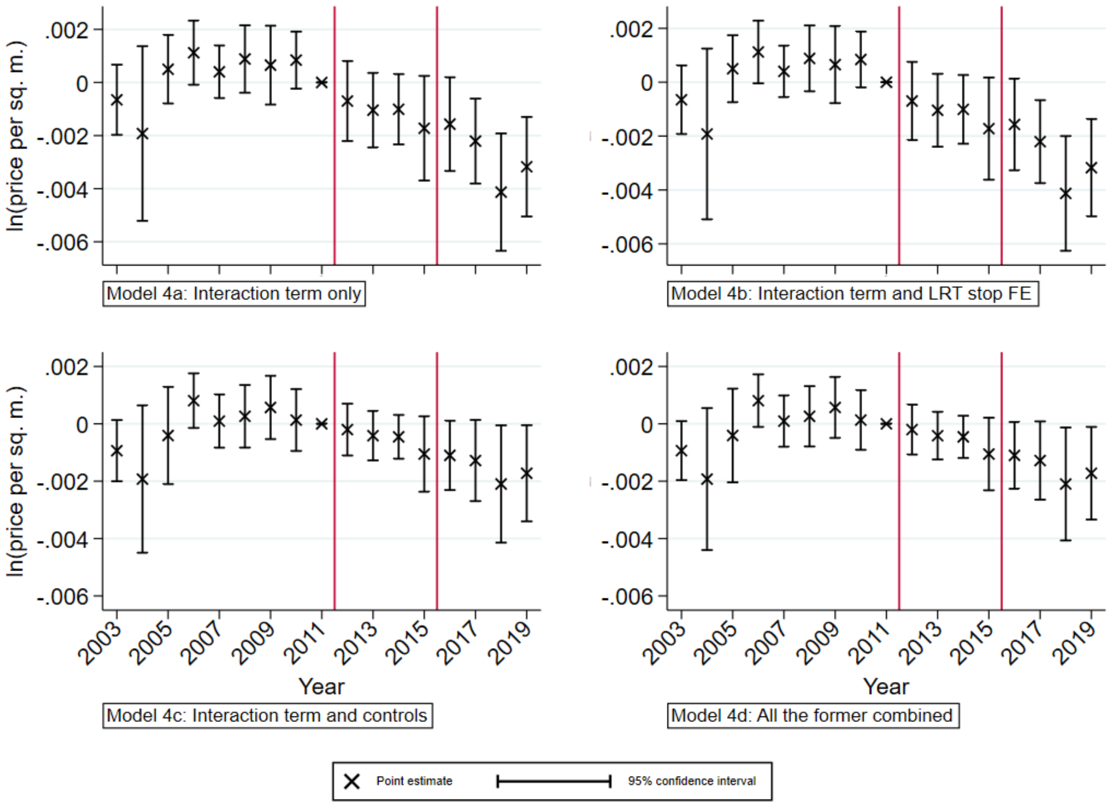
Note. Detailed results are presented in Table B3 in Appendix B. The reference group is transactions over 800 meters away from Jokeri Light Rail stops and the year 2011. The vertical lines represent possible moments of capitalization (see Section 3.1).

A surge in the prices within 800 meters of the stops in 2017–2019 can be distinguished in Figure 4. A more precise analysis of the results shows that prices are 4.5–6.2 percent higher in 2017–2019 within the buffer zones than outside. The point estimates are relatively robust for additional controls as the estimates are statistically significant.

In models 4a–d, I estimate the yearly effects using a continuous distance variable. I present the point estimates for the interaction terms and their 95 percent confidence intervals in Figure 5. Model 4a contains the interaction term solely. In model 4b, I control the former using LRT stop fixed effects. Model 4c combines the interaction term and additional apartment characteristics. Model 4d is a combination of all the former. Here the reference group is observations in 2011.

It can be observed in Figure 5 that moving farther away from the stops lowers the prices from2015 onward. The most potent effect is observable in 2018–2019, when the price reduction is 0.19–0.23 percent *per* hundred meters. These estimates are statistically significant at the 5 percent level. Moreover, the wild bootstrap tests bolster these results.

Figure 5: *Models 4a–d. The yearly impact of Jokeri Light Rail with continuous distance*



Note. Detailed results are presented in Table B4 in Appendix B. The reference group is the year 2011. The vertical lines represent possible moments of capitalization (see Section 3.1).

5.3 Alternative specifications

I conduct balancing tests to account for possible sorting, e.g., more affluent households might buy higher quality homes close to the investment, which affects the sales composition. The tests (refer to Table 2) show that, on average, the dwellings in both the treatment and the control group are statistically similar in terms of observable characteristics. Moreover, I further assess the anticipation effect using alternative distance bands. Of all the models estimated, model 3d[5] has the most statistical power.

I test a modification of model 3d, where I adopt 200-meter bands instead of the original 800-meter ones (see Figure A2 in Appendix A). However, as the yearly number of observations in the 200-meter bands is relatively low, I divide the observations into eight year groups. The reference group in model 5 is observations over 3,000 meters away from the stops and in 2010–2011. Extensive results are shown in Table B5 in Appendix B.

Figure A2 illustrates that the anticipation effect is most abundant in 2018–2019. The positive impact of the investment is observable within 800 meters of the stops. This observation supports the usage of the 800-meter buffer zones as in models 1 and 3. The most substantial impact is felt 0–200 meters from the stops, where the prices are 8.2 percent higher in 2018–2019 than over 3,000 meters away. The impact is between 5 to 7 percent within 200–800 meters of the stops.

[5] *Model 3d estimates yearly effects in two distance groups and includes apartment characteristics and postal code fixed effects, too.*

6. Discussion

When estimating the anticipation effect using the 800-meter catchment areas and a before-and-after setting in model 1, I observe that apartment prices are 4.6 percent higher after 2016 within the 800-meter buffer zones than outside them. In model 3, where I estimate yearly effects, the impact is even more substantial at 4.5–6.2 percent. The latter estimate is notably robust and statistically significant. Higher standard errors closer to the start of operations may be due to dwellings or areas becoming more dissimilar from one another.

However, there may be an alternative explanation for the results. The general house price development cannot be held responsible because I have deflated the prices to the 2019 level using the CPI, and I also incorporate year fixed effects in some of my models. The estimated price increase is probably not due to housing price development near extensive traffic connections either: the control group of my study includes observations where the connections are even more extensive, and thus the urban development is more intense.

The shifts in supply and demand from outside the buffer zones to the inside might have a considerable effect on the estimates. However, Figure A1 in Appendix A depicts no evident supply or demand shifts: the yearly transaction share is relatively stable inside and outside the 800-meter buffer zones. Moreover, although I have omitted new buildings from my sample, it may well be that Jokeri Light Rail will increase the supply of new housing near the investment, affecting the demand for old housing. Nevertheless, I consider this unlikely to have happened so soon.

I present the yearly housing transactions of new buildings in Figure A3 in Appendix A, displaying only a slight increase in sales. Furthermore, if the sales of new apartments increased substantially, my models would underestimate the actual anticipation effect rather than overestimate it.

Dubé et al. (2018) find similar results when studying a rail investment's anticipation effect within 600 meters of stations. Furthermore, Harjunen (2018) observes a 4-percent price premium within 800 meters of metro stations. However, Ransom (2018) finds no significant effects from an LRT investment, though the results vary spatially. All these three studies utilize a difference-in-differences strategy, which makes them good benchmarks for my paper.

When measuring the distance to the stops using a continuous variable, in models 2 and 4, I estimate that housing prices fall by 0.19–0.23 percent for each 100-meter increase in distance to the stops in 2018–2019. These estimates are relatively robust for alternative controls and statistically significant. Even though the number of clusters in these models is only 34, the wild bootstrap tests imply that the significance levels reported are robust.

Dai et al. (2016) find that each hundred meters away from metro stations substantially reduces property prices. However, several studies imply spatial variance in the effect when measuring the distance to the stations continuously. Camins-Esakov and Vandegrift (2018) do not detect any significant effect when assessing the impact of an LRT. In addition, Papon et al. (2015) find that a rail investment may also have a negative effect near the stations.

Moreover, there may be several factors affecting my estimates. Firstly, the shape of the LRT line is an arc around the CBD, which means the accessibility improvements, especially in the regional centers, are not maximized (see Mulley and Tsai 2016). Furthermore, the same route has been operated by a BRT line, and as an LRT, Jokeri Light Rail will not reach as high a service level as a heavy rail line would.

Secondly, the public's information about Jokeri Light Rail is imperfect. The information asymmetry regarding the operations' expected beginning, as the planned start is still many years away, and its impact on other public transportation is unclear. Thus, it might be difficult for the public to anticipate the investment accurately.

Thirdly, the research design may pose problems for validity. It is unlikely that the effects of Jokeri Light Rail end 800 meters from the stops. However, as model 5 shows, 800 meters is the best choice for the buffer zones. The bias is most likely positive as the apartments outside the primary catchment areas used in this study also benefit from the investment.

In this study, I measure the Euclidean distances to the stops, which do not admit any geographical obstacles such as highways or waterways. While I estimate the average treatment effect of Jokeri Light Rail, I surmise that the price changes will be the most drastic in areas where accessibility improves the most (see Diaz and Mclean 1999).

However, observations located over 800 meters from the stops, the primary control group of this study, might not provide the optimal counterfactual. The chosen control group can significantly impact the observed housing market effect (Pilgram and West 2018). Finally, my data cover only six months of transactions after the construction of Jokeri Light Rail started: the actual anticipation effect may be observed at the beginning of the 2020s.

A clear majority of the observations belong to the control group (see Table 2). While I assume the demand to shift from the control group to the treatment group, the fall in demand in the former might not be substantial as the price level has increased in both groups. Ultimately, long-term price changes are likely to exceed the short-term ones in both groups so that the eventual price effect will be greater than the anticipation effect estimated in this study.

6.1 A rough estimate of the total value of capitalization

The cost estimate for Jokeri Light Rail's construction is 386 million euros (Jokeri Light Rail 2019). Here, I provide a feasible estimate for the return on the investment. I assume that the housing transaction data is a representative sample of the total housing stock.

The average impact of Jokeri Light Rail on the square meter prices within 800 meters of the stops in 2019 is 4.95 percent (see Table B3 in Appendix B)[6]. The average square meter price of those apartments is 3,569 euros (Central Federation of Finnish Real Estate Agencies). The existing housing stock within the buffer zones consists of 2.19 million square meters of floor area in 2018 (Registry data: SeutuCD'18).

Therefore, the estimated total windfall generated is between 80 and 723 million euros; when using the point estimate, the estimated value is 396 million. Although it is unclear whether the appreciation of housing stock is distributed optimally, some gain most likely contributes to increased real-estate tax revenue.

My estimate should be taken with some trepidation because I might have overestimated the impact of Jokeri Light Rail due to demand shifts. However, the estimate does not consider the capitalization in commercial properties[7]. For example, there were nearly 850,000 square meters of floor area in office buildings within the catchment areas in 2018 (Registry data: SeutuCD'18). Moreover, I neither explicitly consider possible externalities in this assessment: Jokeri Light Rail may impact, e.g., the number of jobs and traffic congestion.

7. Conclusions

In this paper, I analyze how the political decision of constructing Jokeri Light Rail in Espoo and Helsinki affects the local housing markets between 2003 and 2019. I study whether the housing markets anticipate improved accessibility and forthcoming urban development. To achieve this, I utilize micro-level housing transaction data combined with a difference-in-differences identification strategy. As an added control, I include housing and neighborhood characteristics in my models.

My results imply that the anticipation effect is detectable in the housing markets of Espoo and Helsinki. The positive impact is statistically significant in 2016–2019 when the public had enough information about the investment and its ascertainment, i.e., five to eight years before the operation's planned beginning. Most studies regarding rail investment's

[6] The 95 percent confidence interval's lower bound is 1.02 percent, while the upper bound is 8.87 percent.

[7] A majority of studies have found that the impact of rail investment on commercial properties is positive (Debrezion et al. 2007; Gupta et al. 2020).

effect on the housing market reach similar conclusions, which is on par with urban economics theories on land value capitalization. However, the results seem to be conditional on the research framework.

I find that the intensity of Jokeri Light Rail's anticipation effect depends on the distance to the stops: the effect is observed most distinctly within 800 meters. The prices of apartments within the 800-meter buffer zones around the stops are, on average, 5 percent higher compared to apartments farther away in 2019. Furthermore, I demonstrate that the average price decrease is around 0.2 percent for each hundred-meter increase in distance to the stops.

My rough estimate for the total windfall for homeowners is 396 million euros, which exceeds the cost estimate for the investment. This hike in housing values reflects households' increased willingness to pay to live near the investment. Moreover, the benefits will most likely increase in the future due to heightened urban development. Besides, the estimate for the total windfall ignores the impact on commercial properties.

My estimates must be regarded with certain reservations. In addition to possibly unrealistic assumptions, there is some level of uncertainty related to the estimates. Standard errors increase the closer the start of operations becomes, perhaps due to observations becoming more dissimilar to each other. While possible externalities are omitted from the explicit analysis, the estimates seem robust when considering different distance bands. Moreover, I find that supply changes, which might distort the results, are, at the most, minor.

This paper can help decision-makers assess new rail investments, especially in Finland, since the housing price increase means demand for dwellings is higher near rail investments. However, I cannot definitely state whether the decision to build Jokeri Light Rail is efficient. Nevertheless, under the assumptions made, my study indicates that property values increase substantially due to the investment and that those benefits outweigh the investment costs.

It would be crucial to increase the number of similar studies conducted, especially in the Finnish context. For instance, the operations phase of West Metro's first stage or the construction phase of West Metro's second stage could be used to measure the efficacy of a rail investment further. Finally, combining a quasi-experimental design with cell phone ping or individual-level data could provide the ultimate tool for assessing an investment's suitability.

References

Alonso, W. (1964), *Location and land use: Toward a general theory of land rent*, Harvard University Press, Cambridge.

Ashenfelter, O. C. and Card, D. (1984), "Using the longitudinal structure of earnings to estimate the effect of training programs", *Review of Economics and Statistics*, 67(4), pp. 648–660.

Billings, S. B. (2011), "Estimating the value of a new transit option", *Regional Science and Urban Economics*, 41(6), pp. 525–536.

Cameron, A. C., Gelbach, J. B. and Miller, D. L. (2008), "Bootstrap-based improvements for inference with clustered errors", *The Review of Economics and Statistics*, 90(3), pp. 414–427.

Camins-Esakov, J. and Vandegrift, D. (2018), "Impact of a light rail extension on residential property values", *Research in Transportation Economics*, 67, pp. 11–18.

Central Federation of Finnish Real Estate Agencies: Housing markets. Retrieved from https://kvkl.fi/ajankohtaista/asuntomarkkinat/ on 21.12.2020.

Central Federation of Finnish Real Estate Agencies, KVKL HSP -hintaseurantapalvelu. Retrieved from https://www.hintaseurantapalvelu.fi/ on 3.1.2020.

City of Vantaa (2019), Vantaan ratikan yleissuunnitelma. Retrieved from https://www.vantaa.fi/instancedata/prime_product_julkaisu/vantaa/embeds/vantaaw wwstruc- ture/147683_Vantaan_ratikan_yleissuunnitelma_raportti.pdf on 3.12.2019.

Consumer Price Index (2020), ISSN=1796-3524. Statistics Finland, Helsinki. Retrieved from http://www.stat.fi/til/khi/index.html on 4.2.2020.

Dai, X., Bai, X. and Xu, M. (2016), "The influence of Beijing rail transfer stations on surrounding housing prices", *Habitat International*, 55, pp. 79–88.

Debrezion, G., Pels, E. and Rietveld, P. (2007), "The impact of railway stations on residential and commercial property value: a meta-analysis", *The Journal of Real Estate Finance and Economics*, 35(2), pp. 161–180.

Diaz, R. B. and Mclean, V. A. (1999), "Impacts of rail transit on property values", American Public Transit Association Rapid Transit Conference Proceedings, pp. 1–8.

Dubé, J., Legros, D. and Devaux, N. (2018), "From bus to tramway: Is there an economic impact of substituting a rapid mass transit system? An empirical investigation accounting for anticipation effect", *Transportation Research Part A: Policy and Practice*, 110, pp. 73–87.

European Commission (2017), Housing market developments. European semester thematic factsheet. Retrieved from https://ec.europa.eu/info/sites/info/files/file_import/europeansemester_thematic- factsheet_housing-market-developments_en.pdf on 17.3.2020.

Fesselmeyer, E. and Liu, H. (2018), "How much do users value a network expansion? Evidence from the public transit system in Singapore", *Regional Science and Urban Economics*, 71, pp. 46–61.

General Guide Map of the City of Helsinki. The maintainer of the dataset is Helsingin kaupunkiym- päristön toimiala / Kaupunkimittauspalvelut. The dataset has been downloaded from Helsinki Region Infoshare service on 10.2.2020 under the license Creative Commons Attribution 4.0. Retrieved from https://hri.fi/data/fi/dataset/helsingin-yleiskartta.

Gibbons, S. and Machin, S. (2005), "Valuing rail access using transport innovations", *Journal of urban Economics*, 57(1), pp. 148–169.

Google Trends (2020), Google. Retrieved from https://trends.google.com/trends/?geo=FI on 29.1.2020.

Gupta, A., Van Nieuwerburgh, S. and Kontokosta, C. (2020), "Take the Q Train: Value Capture of Public Infrastructure Projects", No. w26789, National Bureau of Economic Research.

Harjunen, O. (2018), "Metro investment and the housing market anticipation effect", Working Papers 2018:2, City of Helsinki.

James, O. (2009), "Evaluating the expectations disconfirmation and expectations anchoring approaches to citizen satisfaction with local public services", *Journal of public administration research and theory*, 19(1), pp. 107–123.

Jokeri Light Rail (2009), Alustava yleissuunnitelma. Retrieved from http://raidejokeri.info/wp- content/uploads/2015/05/Raide-Jokeri_raportti.pdf on 22.12.2019.

Jokeri Light Rail (2016a), Raide-Jokerin hankesuunnitelma valmis päätöksentekoon. Retrieved from https://raidejokeri.info/raide-jokerin-hankesuunnitelma-valmis-paatoksentekoon/ on 23.12.2019.

Jokeri Light Rail (2016b), Valtuustot näyttivät vihreää valoa Raide-Jokerille. Retrieved from https://raidejokeri.info/valtuustot-nayttivat-vihreaa-valoa-raide-jokerille/ on 23.12.2019.

Jokeri Light Rail (2019), Raide-Jokerin toteutus etenee kaupunkien päätöksentekoon. Retrieved from https://raidejokeri.info/raide-jokerin-toteutus-etenee-kaupunkien-paatoksentekoon/ on 3.12.2019.

Jokeri Light Rail: Construction. Retrieved from https://raidejokeri.info/rakentaminen/ on 23.12.2019. Jokeri Light Rail: Information. Retrieved from https://raidejokeri.info/mika-raide-jokeri/ on 22.12.2019.

Kain, J. F. and Quigley, J. M. (1975), "A theory of urban housing markets and spatial structure", in *Housing markets and racial discrimination: a microeconomic analysis*, pp. 9–55, National Bureau of Economic Research.

Ke, Y. and Gkritza, K. (2019), "Light rail transit and housing markets in Charlotte-Mecklenburg County, North Carolina: Announcement and operations effects using quasi-experimental methods", *Journal of Transport Geography*, 76, pp. 212–220.

Laakso, S. (1992), "Public transport investment and residential property values in Helsinki", *Scandinavian Housing and Planning Research*, 9(4), pp. 217–229.

Laakso, S. and Loikkanen, H. A. (2013), "Helsingin seudun maankäyttö, kiinteistömarkkinat ja perusrakenteen rahoitus", *Kansantaloudellinen aikakauskirja*, 109(4), pp. 490–511.

Laakso, S. and Loikkanen, H. A. (2016), "Tiivistyvä kaupunkikehitys. tuottavuuden ja hyvinvoinnin kasvun perusta", Tehokkaan Tuotannon Tutkimussäätiö, Helsinki.

Lewis, G. and Bajari, P. (2011), "Procurement contracting with time incentives: Theory and evidence", *The Quarterly Journal of Economics*, 126(3), pp. 1173–1211.

McDonald, J. F. and Osuji, C. I. (1995), "The effect of anticipated transportation improvement on residential land values", *Regional science and urban economics*, 25(3), pp. 261–278.

Mohammad, S. I., Graham, D. J. and Melo, P. C. (2017), "The effect of the Dubai Metro on the value of residential and commercial properties", *Journal of Transport and Land Use*, 10(1), pp. 263–290.

Mohammad, S. I., Graham, D. J., Melo, P. C. and Anderson, R. J. (2013), "A meta-analysis of the impact of rail projects on land and property values", *Transportation Research Part A: Policy and Practice*, 50, pp. 158–170.

Mulley, C. and Tsai, C. H. (2016), "When and how much does new transport infrastructure add to property values? Evidence from the bus rapid transit in Sydney, Australia", *Transport policy*, 51, pp. 15–23.

Muth, R. F. (1969), *Cities and housing*, University of Chicago Press, Chicago.

Olszewski, P. and Wibowo, S. S. (2005), "Using equivalent walking distance to assess pedestrian accessibility to transit stations in Singapore", *Transportation research record*, 1927(1), pp. 38–45.

Papon, F., Nguyen-Luong, D. and Boucq, E. (2015), "Should any new light rail line provide real estate gains, or not? The case of the T3 line in Paris", *Research in Transportation Economics*, 49, pp. 43–54.

Parmeter, C. F. and Pope, J. C. (2013), "Quasi-Experiments and Hedonic Property Value Methods", in *Handbook on experimental economics and the environment*, eds. List, J. A. – Price, M. K., pp. 3–66, Edward Elgar Publishing, Cheltenham.

Pilgram, C. A. and West, S. E. (2018), "Fading premiums: The effect of light rail on residential property values in Minneapolis, Minnesota", *Regional Science and Urban Economics*, 69, pp. 1–10.

Project assessment of Jokeri Light Rail (2019), FLOU Oy. Retrieved from https://raidejokeri.info/wp- content/uploads/2019/01/RJ_000_KPT-PRJ_Raportti-hankearviointi-ID-24372.pdf on 3.4.2021.

Ransom, M. R. (2018), "The effect of light rail transit service on nearby property values", *Journal of Transport and Land Use*, 11(1), pp. 387–404.

Registry data: SeutuCD'18, HSY and Statistics Finland, 2018.

Rosen, S. (1974), "Hedonic prices and implicit markets: product differentiation in pure competition", *Journal of political economy*, 82(1), pp. 34–35.

Tenkanen, H., Espinosa, J.L., Willberg, E., Heikinheimo, V., Tarnanen, A., Jaakkola, T., Järvi, J., Salonen, M. and Toivonen, T. (2018), Helsinki Region Travel Time Matrix 2018. DOI: 10.13140/RG.2.2.20858.39362

Vuori, P. and Kaasila, M. (2019), "Helsingin ja Helsingin seudun väestöen- nuste 2019–2050", Helsingin kaupunki, Tilastoja, 14. Retrieved from https://www.hel.fi/hel2/tietokeskus/julkaisut/pdf/19_10_25_Tilastoja_14_Vuori_Kaasila.pdf on 6.1.2020.

Weisbrod, G., Mulley, C. and Hensher, D. (2016), "Recognising the complementary contributions of cost benefit analysis and economic impact analysis to an understanding of the worth of public transport investment: A case study of bus rapid transit in Sydney, Australia", *Research in Transportation Economics*, 59, pp. 450–461.

Zhou, Z., Chen, H., Han, L. and Zhang, A. (2019), "The effect of a subway on house prices: Evidence from Shanghai", *Real Estate Economics*, 49(S1), pp. 199–234.

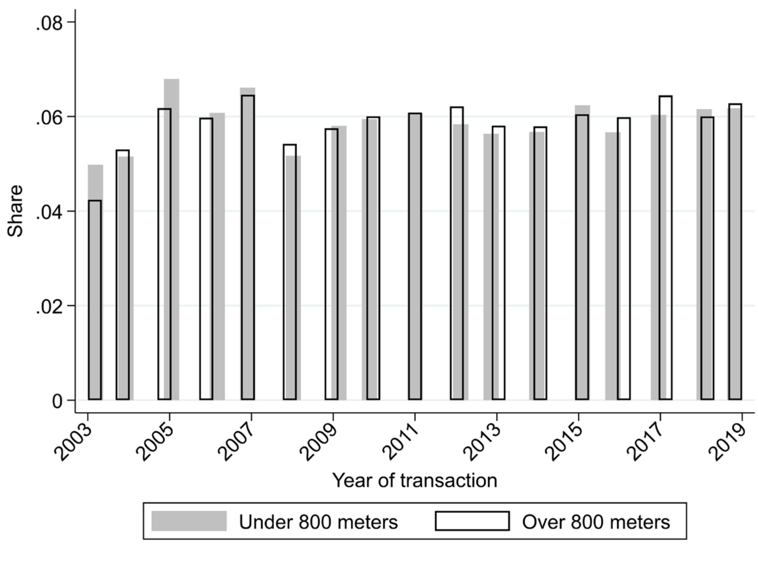
A Appendix: Data appendix

Table A1: *Postal code areas included in this study*

	Helsinki		Espoo
00200	00420	00780	02100
00230	00430	00790*	02110
00240	00440	00800*	02120
00270	00560	00810	02130*
00280	00600	00820	02140*
00300	00610	00830	02150*
00310	00620*	00880*	02160
00320*	00630*	00900*	02180
00340	00640*	00910	02200
00350*	00650*	00920*	02600*
00360*	00660	00930*	02610
00370*	00670	00940	02620
00380*	00680	00950	02630
00390	00700	00980	02650
00400*	00710*		02660
00410	00720		02680
	46 areas		16 areas

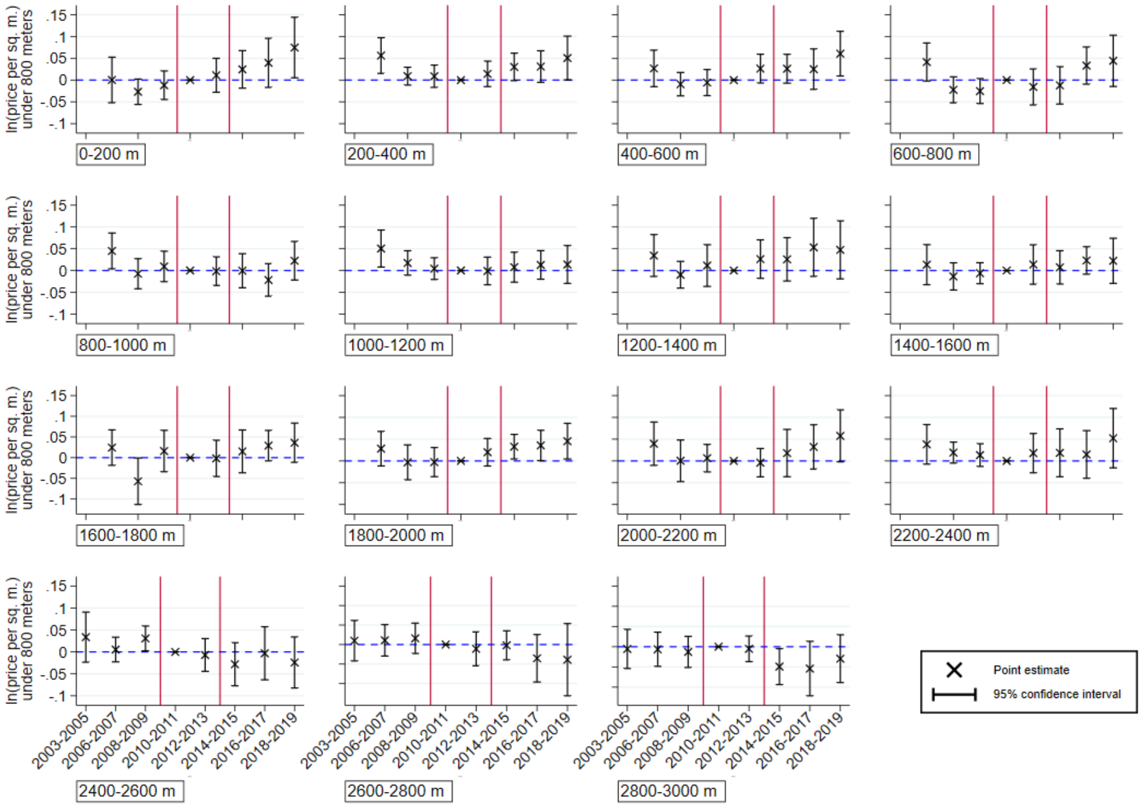
*Note. Postal code areas that contain Jokeri Light Rail stops marked with *.*

Figure A1: *The yearly share of housing transactions in the treatment and control group between 2003 and 2019*



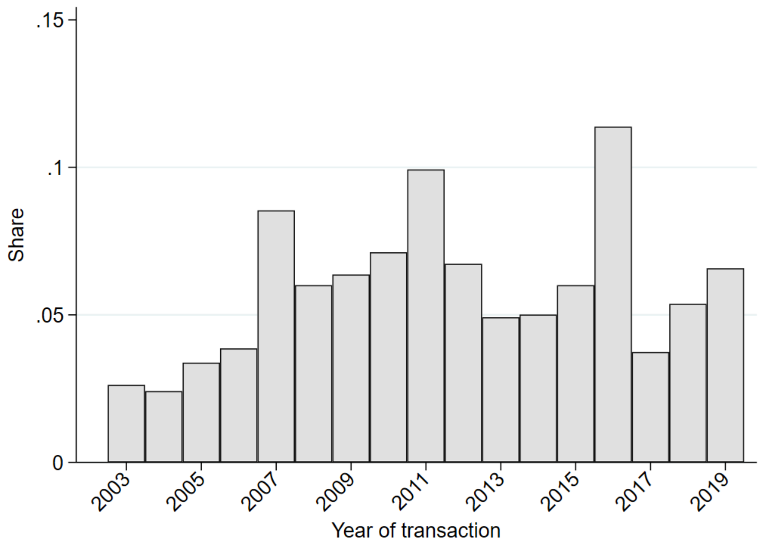
Note. Here, the share of transactions during the whole period sum up to one separately for both distance groups.

Figure A2: *Model 5. Housing market effect in 200-meter bands and year groups*



Note. Model 5 is a modification of model 3d; here, I have divided observations into 200-meter bands and adopt two-year groups instead. Vertical lines represent possible moments of capitalization (see Section 3.1). Zero marked with a blue dashed line.

Figure A3: *The yearly share of housing transactions of new apartments between 2003 and 2019 in postal code areas where Jokeri Light Rail stops are located*



Note. The transactions of December 2019 are excluded due to data availability.

B Appendix: Regression tables for models 1–5

Table B1: *Model 1. Housing market effect in two distance groups before and after 2016*

Response variable: ln(price per square meter)	**Reference group: over 800 meters and before 2016**			
	(1a)	**(1b)**	**(1c)**	**(1d)**
Under 800 m*After	0.0486* (0.0252)	0.0502* (0.0265)	0.0342* (0.0179)	0.0456** (0.0205)
Under 800 m	-0.00977 (0.0516)	0.00277 (0.0164)	0.00689 (0.0263)	-0.0181 (0.0113)
After	0.139*** (0.0158)	0.144*** (0.0173)	0.117*** (0.0144)	0.139*** (0.0128)
Travel time	–	–	-0.0121*** (0.00211)	-0.00133 (0.00122)
Age	–	–	-0.0183*** (0.00205)	-0.0159*** (0.00121)
Age^2	–	–	0.000246*** (2.90e-05)	0.000180*** (1.78e-05)
Floor area	–	–	-0.00321*** (0.000383)	-0.00340*** (0.000302)
Freehold site	–	–	0.144*** (0.0201)	0.0658*** (0.00845)
Maint. charge (€/m^2)	–	–	0.00321 (0.00419)	0.000955 (0.00298)
Condition FE	No	No	Yes	Yes
Building type FE	No	No	Yes	
Intercept	8.089*** (0.0441)	8.101*** (0.0191)	8.911*** (0.0654)	8.645*** (0.0570)
Postal code FE	No	Yes	No	Yes
N	63,745	63,745	63,745	63,745
R^2	0.061	0.061	0.476	0.316

*Note. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. Before-period is 2003–2012, after-period is 2016–2019. Observations from 2013–2015 are not used. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the postal code level (62) are reported in parentheses.*

Table B2: *Model 2. Housing market effect with continuous distance before and after 2016*

Response variable: ln(price per square meter)	**Reference group: before 2016**					
	(2a) reg	**(2b) xtreg**	**(2b.II) reg with wbs**	**(2c) reg**	**(2d) xtreg**	**(2d.II) reg with wbs**
Distance*After	-0.00309*** (0.000689) [0.000]	-0.00269** (0.00107) –	-0.00269** (0.00107) [0.025]	-0.00157** (0.000727) [0.038]	-0.00207** (0.000888) –	-0.00207** (0.000889) [0.029]
Distance	0.00172 (0.00299)	0.00200 (0.00173)	0.00201 (0.00173)	-0.00150 (0.00117)	-0.000368 (0.00108)	-0.000364 (0.00108)
After	0.204*** (0.0172)	0.205*** (0.0193)	0.205*** (0.0194)	0.152*** (0.0149)	0.179*** (0.0150)	0.179*** (0.0150)
Travel time	–	–	–	-0.0125*** (0.00204)	-0.0078*** (0.00136)	-0.00575*** (0.00137)
Age	–	–	–	-0.0186*** (0.00194)	-0.0176*** (0.00106)	-0.0176*** (0.00106)
Age^2	–	–	–	0.000249*** (2.75e-05)	0.000209*** (1.59e-05)	0.000209*** (1.59e-05)
Floor area	–	–	–	-0.00321*** (0.000470)	-0.00331*** (0.000378)	-0.00332*** (0.000377)
Freehold site	–	–	–	0.148*** (0.0225)	0.0742*** (0.0123)	0.740*** (0.123)
Maint. charge (€/m²)	–	–	–	0.00420 (0.00437)	0.00277 (0.00283)	0.00274 (0.00282)
Condition FE	No	No	No	Yes	Yes	Yes
Building type FE	No	No	No	Yes	Yes	Yes
Intercept	8.057*** (0.0349)	8.056*** (0.0301)	8.319*** (0.0486)	8.954*** (0.0579)	8.772*** (0.0588)	9.001*** (0.0575)
RT stop FE	No	Yes	Yes	No	Yes	Yes
N	63,745	63,745	63,745	63,745	63,745	63,745
R^2	0.063	0.063	0.417	0.480	0.409	0.642

*Note. reg and xtreg refer to the command used; wbs corresponds to wild bootstrap. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. Before-period is 2003–2012, after-period is 2016–2019. Observations from 2013–2015 are not used. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the LRT stop level (34) are reported in parentheses. The p-value for the wild bootstrap is reported in square brackets.*

Table B3: *Model 3. Yearly housing market effect in two distance groups*

Response variable: ln(price per square meter)	Reference group: over 800 meters and year 2011			
	(3a)	(3b)	(3c)	(3d)
Under 800 m*2003	0.00938 (0.0168)	0.0134 (0.0165)	0.00926 (0.0124)	0.0159 (0.0116)
Under 800 m*2004	0.0170 (0.0202)	0.0150 (0.0172)	0.0103 (0.0166)	0.00885 (0.0143)
Under 800 m*2005	-0.00995 (0.0144)	0.00402 (0.0191)	-0.00172 (0.0119)	0.00397 (0.0145)
Under 800 m*2006	-0.00765 (0.0180)	-0.00861 (0.0149)	-0.0177 (0.0122)	-0.00805 (0.0115)
Under 800 m*2007	0.00551 (0.0159)	-0.00162 (0.0175)	-0.00743 (0.00964)	-0.00381 (0.0136)
Under 800 m*2008	-0.0231 (0.0148)	-0.00801 (0.0163)	-0.0214* (0.0123)	-0.00708 (0.0133)
Under 800 m*2009	-0.0160 (0.0140)	0.00198 (0.0148)	-0.0229** (0.0102)	-0.00258 (0.0111)
Under 800 m*2010	-0.0143 (0.0115)	-0.00834 (0.0125)	-0.0113 (0.00913)	-0.00657 (0.0101)
Under 800 m*2012	-0.00259 (0.0152)	0.0146* (0.00859)	-0.00420 (0.0109)	0.0118* (0.00696)
Under 800 m*2013	0.0214* (0.0117)	0.0185* (0.0103)	0.00381 (0.00937)	0.0145* (0.00853)
Under 800 m*2014	0.0269* (0.0156)	0.0312* (0.0147)	0.00542 (0.0109)	0.0234* (0.0117)
Under 800 m*2015	0.0298 (0.0216)	0.0377** (0.0182)	0.00765 (0.0163)	0.0274* (0.0146)
Under 800 m*2016	0.0122 (0.0222)	0.0225 (0.0217)	0.0104 (0.0157)	0.0224 (0.0162)
Under 800 m*2017	0.0376* (0.0207)	0.0468** (0.0198)	0.0224 (0.0153)	0.0433* (0.0165)
Under 800 m*2018	0.0634** (0.0284)	0.0685*** (0.0228)	0.0399* (0.0219)	0.0593*** (0.0184)
Under 800 m*2019	0.0466* (0.0265)	0.0517** (0.0236)	0.0237 (0.0209)	0.0495** (0.0200)
Under 800 m	-0.00183 (0.0541)	0.00225 (0.0159)	0.0153 (0.0290)	-0.0219* (0.0118)
Control variables	No	No	Yes	Yes
Yearly effects	Yes	Yes	Yes	Yes
Postal code FE	No	Yes	No	Yes
N	77,378	77,378	77,378	77,378
R^2	0.112	0.112	0.525	0.342

*Note. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. The time period is 2003– 2019. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the postal code level (62) are reported in parentheses.*

Table B4: *Model 4. Yearly housing market effect with continuous distance*

Response variable: ln(price per square meter)	**Reference group: year 2011**					
	(4a) reg	**(4b) xtreg**	**(4b.II) reg with wbs**	**(4c) reg**	**(4d) xtreg**	**(4d.II) reg with wbs**
Distance*2003	-0.000652 (0.000650)	-0.000652 (0.000650)	-0.000318 (0.000762)	-0.000936* (0.000525)	-0.000936* (0.000525)	-0.000318 (0.000762)
Distance*2004	-0.00192 (0.00162	-0.00192 (0.00162)	-0.000822 (0.000890)	-0.00193 (0.00126)	-0.00193 (0.00126)	-0.000822 (0.000890)
Distance*2005	0.000499 (0.000634)	0.000499 (0.000634)	-0.000461 (0.00137)	-0.000408 (0.000833)	-0.000408 (0.000833)	-0.000461 (0.00137)
Distance*2006	0.00112* (0.000594)	0.00112* (0.000594)	0.000925 (0.000705)	0.000807* (0.000468)	0.000807* (0.000468)	0.000925 (0.000705)
Distance*2007	0.000402 (0.000487)	0.000402 (0.000487)	0.000349 (0.000697)	9.51e-05 (0.000456)	9.51e-05 (0.000456)	0.000349 (0.000697)
Distance*2008	0.000884 (0.000624)	0.000884 (0.000624)	0.000590 (0.000709)	0.000262 (0.000537)	0.000262 (0.000537)	0.000590 (0.000709)
Distance*2009	0.000653 (0.000730)	0.000653 (0.000730)	0.000423 (0.000840)	0.000571 (0.000543)	0.000571 (0.000543)	0.000423 (0.000840)
Distance*2010	0.000842 (0.000528)	0.000842 (0.000528)	0.000410 (0.000706)	0.000132 (0.000531)	0.000132 (0.000531)	0.000410 (0.000706)
Distance*2012	-0.000699 (0.000740)	-0.000699 (0.000740)	-0.00083 (0.000515)	-0.000202 (0.000444)	-0.000202 (0.000444)	-0.00083 (0.000515)
Distance*2013	-0.00104 (0.000690)	-0.00104 (0.000690)	-0.00106* (0.000486)	-0.000413 (0.000424)	-0.000413 (0.000424)	-0.00106** (0.000486)
Distance*2014	-0.00101 (0.000651)	-0.00101 (0.000651)	-0.00135* (0.000585)	-0.000454 (0.000375)	-0.000454 (0.000375)	-0.00135** (0.000585)
Distance*2015	-0.00172* (0.000968)	-0.00172* (0.000968)	-0.00146 (0.000840)	-0.00105 (0.000646)	-0.00105 (0.000646)	-0.00146* (0.000840)
Distance*2016	-0.00157* (0.000867)	-0.00157* (0.000867)	-0.00186* (0.000831)	-0.00110* (0.000594)	-0.00110* (0.000594)	-0.00186** (0.000831)
Distance*2017	-0.00221*** (0.000786)	-0.00221*** (0.000786)	-0.00205** (0.000826)	-0.00128* (0.000696)	-0.00128* (0.000696)	-0.00205** (0.000826)
Distance*2018	-0.00413*** (0.00109)	-0.00413*** (0.00109)	-0.00311*** (0.000942)	-0.00210** (0.00101)	-0.00210** (0.00101)	-0.00311*** (0.000942)
Distance*2019	-0.00317*** (0.000921) [0.001]	-0.00317*** (0.000921) –	-0.00281*** (0.00100) [0.004]	-0.00172** (0.000824) [0.047]	-0.00172** (0.000824) –	-0.00281*** (0.00100) [0.007]
Distance	0.00142 (0.00304)	0.00142 (0.00304)	0.00180 (0.00189)	-0.00148 (0.00129)	-0.00148 (0.00129)	0.00180 (0.00189)
Control variables	No	No	No	Yes	Yes	Yes
Yearly effects	Yes	Yes	Yes	Yes	Yes	Yes
LRT stop FE	No	Yes	Yes	No	Yes	Yes
N	77,378	77,378	77,378	77,378	77,378	77,378
R^2	0.114	0.114	0.207	0.530	0.530	0.702

*Note. reg and xtreg refer to the command used; wbs corresponds to wild bootstrap. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. The time period is 2003–2019. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the LRT stop level (34) are reported in parentheses. The p-value for the wild bootstrap is reported in square brackets.*

Table B5: *Model 4. Housing market effect in 200-meter bands*

Response variable: ln(price per square meter)	**Reference group: over 3 000 meters and 2010–2011**						
	2003–2005	**2006–2007**	**2008–2009**	**2012–2013**	**2014–2015**	**2016–2017**	**2018–2019**
0–200 m	0.00293 (0.0267)	-0.0268* (0.0149)	-0.0118 (0.0167)	0.0110 (0.0199)	0.0245 (0.0220)	0.0395 (0.0287)	0.0747** (0.0355)
200–400 m	0.0562** (0.0209)	0.00899 (0.0104)	0.00883 (0.0131)	0.0142 (0.0149)	0.0302* (0.0161)	0.0310* (0.0185)	0.0506** (0.0256)
400–600 m	0.0267 (0.0214)	-0.00942 (0.0137)	-0.00573 (0.0153)	0.0263 (0.0169)	0.0260 (0.0169)	0.0251 (0.0237)	0.0606** (0.0262)
600–800 m	0.0415* (0.0223)	-0.0224 (0.0152)	-0.0253* (0.0146)	-0.0158 (0.0211)	-0.0122 (0.0219)	0.0333 (0.0218)	0.0442 (0.0300)
800–1 000 m	0.0450** (0.0210)	-0.00740 (0.0177)	0.00937 (0.0178)	-0.00151 (0.0167)	-0.000576 (0.0200)	-0.0216 (0.0191)	0.0224 (0.0226)
1 000–1 200 m	0.0504** (0.0217)	0.0173 (0.0143)	-0.000432 (0.0127)	-0.00104 (0.0162)	0.00759 (0.0176)	0.0128 (0.0167)	0.0138 (0.0222)
1 200–1 400 m	0.0344 (0.0245)	-0.00974 (0.0156)	0.0114 (0.0244)	0.0262 (0.0225)	0.0256 (0.0254)	0.0532 (0.0340)	0.0473 (0.0340)
1 400–1 600 m	0.0133 (0.0235)	-0.0136 (0.0159)	-0.00624 (0.0123)	0.0137 (0.0231)	0.00717 (0.0195)	0.0231 (0.0161)	0.0222 (0.0264)
1 600–1 800 m	0.0243 (0.0219)	-0.0571** (0.0286)	0.0160 (0.0255)	-0.00180 (0.0224)	0.0152 (0.0264)	0.0291 (0.0188)	0.0361 (0.0242)
1 800–2 000 m	0.0282 (0.0202)	-0.00320 (0.0204)	-0.00264 (0.0171)	0.0200 (0.0161)	0.0327** (0.0144)	0.0356** (0.0178)	0.0454** (0.0209)
2 000–2 200 m	0.0396 (0.0254)	0.00347 (0.0243)	0.00634 (0.0161)	-0.00402 (0.0166)	0.0181 (0.0277)	0.0322 (0.0259)	0.0575* (0.0304)
2 200–2 400 m	0.0381 (0.0232)	0.0191 (0.0123)	0.0134 (0.0133)	0.0179 (0.0230)	0.0187 (0.0280)	0.0149 (0.0279)	0.0522 (0.0348)
2 400–2 600 m	0.0336 (0.0291)	0.00535 (0.0143)	0.0307** (0.0144)	-0.00708 (0.0190)	-0.0281 (0.0250)	-0.00317 (0.0308)	-0.0241 (0.0297)
2 600–2 800 m	0.0983 (0.0264)	0.0108 (0.0206)	0.0160 (0.0198)	-0.0111 (0.0222)	-0.00199 (0.0190)	-0.0352 (0.0310)	-0.0388 (0.0473)
2 800–3 000 m	-0.00550 (0.0247)	-0.00629 (0.0215)	-0.0130 (0.0196)	-0.00527 (0.0161)	-0.0492** (0.0227)	-0.0540 (0.0344)	-0.0296 (0.0301)
Control variables				Yes			
Distance group coeffs				Yes			
Year group FE				Yes			
Postal code FE				Yes			
N				77,378			
R^2				0.536			

*Note. The interaction terms of model 5 are shown in five columns, one column for each year group. Distances measured to the nearest Jokeri Light Rail stop. The sample is constrained to sales in postal code areas reported in Table A1 in Appendix A. The time period is 2003–2019. Control variables correspond to those reported in Table 2, also taking into account floor area squared. The estimated coefficients statistical significance is marked with * (10%), ** (5%) or *** (1%). Standard errors clustered at the postal code level (62) are reported in parentheses.*