Winter 12-17-2019

The Proximity Effect of the Seattle LINK Public Light Rail on King County Properties

Graham Byron

The Proximity Effect of the Seattle LINK Public Light Rail on King County Properties

Graham Byron

The University of Puget Sound, Tacoma, WA, USA

17 December 2019

Abstract

Seattle has experienced an explosive rise in population in the last decade and there is no sign of this slowing down. There is a wealth of literature surrounding the way in which public transportation has an effect on the surrounding housing values however no hedonic study has been done on public transportation in the Seattle area. This study responds to the lack of analysis done on the effect that public transportation has in King County.

We use a difference-in-differences and hedonic model to test the effect that the LINK light rail has on houses within a one-mile radius, particularly at the Beacon Hill stop. Utilizing data from the King County Assessor's office, we test to see the change in ideal distance from the light rail for three different time periods. Though the results support the stop having a positive impact on houses in close proximity, the data suggests that additional in-depth research and analysis is needed to build a more robust study for the entirety of the LINK line.

1. Introduction

The UN estimates that 68% of the world's population will live in urban areas by 2050. With this rise in population, the issue of transportation and movement is a pressing one that is being addressed by large metropolitan areas. Having easy access to public transportation is very valuable in densely populated urban areas. This can be reflected in changing housing values, as analyzed by Hopkins (2017), where proximity to a public transportation stop was a significant factor in explaining housing values in a number of metropolitan areas. However, there is also evidence that living directly by a given bus or train stop can be undesirable, as there is the potential for increased crime and noise (Bowes, 2001).

This study attempts to determine the optimum distance to a public transportation stop using the example of the LINK Light Rail in Seattle, which opened in 2009. The history of the LINK construction is long and embattled. Beginning in 1999, discussion regarding the light rail was met with many roadblocks- the price of the project was increased from $1.9 billion to $3.8 billion dollars and three years of construction time was added as well (Garber, 2001). In September of 2001, voters approved the 14-mile line, with an estimated cost of $2.1 billion and construction to begin as early as the summer of 2002 (Pryne, 2002). In March of 2002, Sound Transit began acquiring property for construction and in 2009 it operated for the first time, connecting Downtown Seattle to Sea-Tac Airport. The extension from downtown to the University of Washington later opened in early 2016 (Yardley, 2016).

Between 2010 and 2018 Seattle was the fastest-growing city in the U.S, seeing 18.7% increase in population (Guy, 2018). With such an aggressive rise in population, there is an increasing need for public transportation. Approved by voters in 2016, Sound Transit plans to continue their expansion of the LINK light rail, adding three new stations in 2021 (Guy, 2018). The voters actions indicate that they see value in this light rail investment, however there is no quantitative measure that has been done to see whether or not this investment has a positive or negative impact on those that live closest to the LINK light rail stops.

In this paper, we use a hedonic and difference-in-differences model of housing prices in our analysis to measure the effect that the LINK light rail has on real properties in King County. This model takes into consideration the housing characteristics, neighborhood characteristics, and accessibility characteristics to determine the price of a given property. By integrating the distance away from a light rail stop and additional coefficient values, we can see the effect that it has on the property from before the announcement of the light rail, after the announcement and during construction, and after the rail has been in operation for a number of years. Pan (2012) utilizes the hedonic model on the Houston METRORail line and found that the line had significant positive impacts on some properties, but negative impacts on properties closest to the stops. Other studies utilizing this model found mixed results on the effect public transportation has on property values.

Because there hasn't been a hedonic model done on housing values in King County, it is difficult to determine the effect public transportation may have on these property values. This study draws on the model used by Pan and others to measure the effect that proximity to the light rail will have on housing prices. The study utilizes a difference-in-differences model to analyze the true impact of the light rail at different stages of construction. Lastly, this analysis finds the "sweet spot" of proximity away from the light rail in terms of housing appreciation for all three periods. This paper predicts that the implementation of the LINK light rail has a quantitative effect on local property values in the King County area, altering the ideal location from the LINK light rail stop at Beacon Hill.

2. Literature Review

Since investment in public transportation is hypothesized to have a number of economic benefits, continued support of projects like the Seattle LINK are important to a city that has seen explosive growth in the past century and is predicted to continue this growth. Bhatta (2003) examines a number of studies that analyze the economic benefits of investment in public transportation. One of these hypothesized long-run benefits of public transportation investment is an increase in real property values. Contrarily, the only study reviewed by Bhatta regarding the effect of public transportation on housing values did not have any conclusive results. Other studies find more supportive outcomes, indicating that public transportation may have a positive quantitative effect on properties located closest to a rail or bus stop.

As mentioned, a number of studies employ a hedonic model in their analysis. Yu (2017), Pan (2013) and Martinez (2008) utilize this model, using the distance to a given form of transportation. Further, almost every study looks at the final sale value of a home along with the characteristics that each home has such as home square footage, number of bedrooms, and number of bathrooms to name a few. These measures are analyzed to assess the true effect that distance has on a house value.

While many of the base level characteristics are the same, the way in which each of these studies define their spatial variables differ significantly. Yu (2017) conducted a study in Austin, Texas in which the researchers examined properties within a one-mile radius away from transit stops. The intent of doing so was to capture not only the willingness to access the given stop, but to also include access to other roads and forms of transportation captured within the one-mile radius. This is in contrast to Pan (2012) which looked at houses in a quarter-mile, one-mile, two-mile, and three-mile radius. The study looked to capture the impact varying proximities had on a given housing value. One thing to note is that the wide radii used in Pan's study was intended to capture the proximity to the given stops, and not include other forms of transportation that may be within the radii.

Martinez and Viegas (2008) took two approaches to the model. First, they examined an all-or-nothing influence on proximity to public transportation and roads such as freeways, utilizing dummy variables to measure other forms of transportation accessibility. Second, they utilized a decreasing proximity function to entry points of public transportation, meaning that very low travel time to the entry points signified a high value on an accessibility measure and decreased down a reverse s-curve as travel time to a stop increased. The researchers expand on the hedonic model, including a spatial lag model as well. In doing so, their model considers the price of one house in one location and how it is affected by the price of another house in nearby locations. The study concluded that the proximity of a property to a metro line "leads to significant property value changes" and that both the hedonic and spatial lag model resulted in similar coefficients on the dummy variables used (Martinez, 2009). It should be worth noting that the study adds the spatial lag model in an attempt to conduct a more robust analysis, however many studies do not implement this model.

The results of these studies were mixed and there were a number of notable variables that may affect the way in which public transportation has an impact. For example, Bowes (2001) found that there was a significantly positive effect in neighborhoods that had high income, and significantly negative effects in neighborhoods with lower income. However, Pan (2012) found that there were significant positive effects across the board from proximity of the rail station. Further, the average sale price of homes sold within the observed radius, especially between a quarter-mile and three miles distance away, are higher than the average regional sale price. The houses that did not see as significant increase in prices were those located within a ¼ mile radius. This implies that the negative aspects which come along with public transportation (crime, noise) may have had a negative impact on those prices.

Chatham, Tulach, and Kim (2011) find different results with their study on the New Jersey river line. The study looked to find a quantitative justification for investment in public transportation, but found that the short-term impact did not provide this justification- meaning that the money spent on the project did not provide the value appreciation needed to make the case that the investment had value. Further, the net effect across all properties in a five-mile radius experienced a neutral and even negative impact from the investment. This illustrates how the effect of public transportation differs across both geographical area as well as transportation form.

Lastly, studies conducted in foreign countries also found some mixed results. Dorantes (2011) concluded that in Madrid a house located 1000 meters away from the metro stop was valued between 2.18% and 3.18% less than a house right next to the stop, going against the idea the direct proximity is a negative for the house value. Liou (2016) concluded that the distance to Taiwan's mass rapid transport (MRT) did not have a significant influence on house prices in Taipei.

With such variation in the results of each study there is no key determinant in whether or not there will be a positive impact on housing values in a given city. Many of the studies provide a useful foundation for the data and methods that are utilized in this study. Given the explosive growth in Seattle and the lack of research done on the LINK light rail, there is motivation to employ a hedonic model to measure the impact that it may have on surrounding housing values. Further, none of the studies mentioned utilize the difference-in-differences test, as each look at a single year of data. Lastly, none of the studies utilize the coefficient values from their model to find the “sweet spot” away from the light rail in terms of housing appreciation. In conducting this test, we can see the true impact that the Beacon Hill light rail station has on surrounding properties in King County.

3. Data Description

This study is based on housing values, their characteristics and the characteristics around them, and their location in relation to light rail stops on the Seattle LINK. The data found for this study comes from the King County Assessor’s office as well as the LINK light rail website. The Assessor’s office provides housing characteristics along with all sale prices of residential properties dating back two decades. The data includes sale price, sale date, number of bedrooms, number of bathrooms, square footage of the home, square footage of the property, year built, address, latitude, longitude, parcel number, and zip code. There are also other variables that are more subjective, such as condition. Condition is graded on a scale from 1-5 with one being the highest grade condition and five being the worst. This comprehensive dataset allows for the analysis of housing prices using relevant attributes.

Three years of sales data and housing characteristics are chosen for the analysis- 1994, 2005, and 2016. The year 1994 is selected because it is a time before both announcement and construction of the light rail had taken place. The year 2005 is situated between the announcement and opening of the light rail, with the intent to capture the hypothesized change in properties due to the rail construction. The year 2016 is after the opening of the light rail, which may capture the change in properties due to actual usage of the rail. Sale prices are adjusted to 2018 dollars utilizing the average CPI for the years 1994, 2005, and 2016 from the Federal

Reserve Bank of St. Louis (FRED). By utilizing these three distinct years we are able to conduct a difference-in-differences test that will illustrate the change in real prices from each time period.

Utilizing the latitude and longitude of each house and the location of each light rail stop, a spatial measure is made to determine the proximity of each house relative to the Beacon Hill station light rail stop. This allows for a proximity measure to be evaluated in the hedonic model for each house. All houses that are located further than one mile away are eliminated from the dataset to remove the effect of other light rail stations. The data used in this study are the general housing characteristics, the zip code, which will be a proxy for the neighborhood characteristics, and the distance from a given LINK stop to round out the hedonic model. Working in conjunction with the hedonic model is the difference-in-differences model to determine the true effect that the implementation of the light rail has on property values. The tables below define the variable names for the measurements described above.

Table 1. Description of Variables

Variable	Description
AdjPrice	House sale price adjusted to 2018 dollars
Year	The year in which the house was sold in
ZIP5	The zip code in which the house resides
PLUS4	The plus-four code associated with each zip code
LOTSQFT	The total square footage of the lot in which the property resides
Distance	Distance from the Beacon Hill station to a property
Year*Distance	Interaction variable used to determine ideal distance from light rail stop in post-treatment
Distance^2	Interaction variable used to determine ideal distance from light rail stop in pre-treatment
Year*Distance^2	Interaction variable used to determine ideal distance from light rail stop in post-treatment
Stories	The number of floors in a property
SqFtTotLiving	Total square footage of the house
SqFtGarageAttached	Total square footage of the garage, attached to the property
SqFtOpenPorch	Total square footage of uncovered porch area
SqFtEnclosedPorch	Total square footage of covered porch area
SqFtDeck	Total square footage of all porch area
Bedrooms	Number of bedrooms in a property
BathHalfCount	Number of half bathrooms, containing only a sink and toilet
Bath3qtrCount	Number of 3/4 bathrooms, containing only a sink, toilet, and shower
BathFullCount	Number of full bathrooms, containing a sink, toilet, shower, and bath
Condition	The overall rating of well-being of the house, given on a scale of 1-5

Table 2. Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
AdjPrice	360	801,579.400	1,122,453.000	847.039	302,215.500	512,383.100	4,186,895.000
LOTSQFT	360	15,909.460	26,247.110	3,400	5,382.5	13,300	219,542
Distance	360	0.657	0.232	0.066	0.478	0.842	0.997
Stories	360	1.628	0.478	1	1	2	2
SqFtTotLiving	360	2,370.542	845.021	810	1,727.5	2,801.5	6,230
SqFtTotBasement	360	247.514	516.928	0	0	0	2,340
SqFtGarageAttached	360	410.644	270.973	0	237.5	502.5	1,430
SqFtOpenPorch	360	98.814	131.070	0	0	153	750
SqFtEnclosedPorch	360	4.397	34.281	0	0	0	340
SqFtDeck	360	58.606	140.829	0	0	50	1,120
Bedrooms	360	3.589	0.767	0	3	4	7
BathHalfCount	360	0.642	0.497	0	0	1	2
Bath3qtrCount	360	0.306	0.529	0	0	1	3
BathFullCount	360	1.769	0.573	0	1	2	4
Condition	360	3.369	0.583	2	3	4	5

4. Model and Econometric Techniques

To test the effect of proximity on housing values, this study utilizes a hedonic model. The model combines all of the variables into three umbrella variables. The first set of variables are housing characteristics, which consists of the number of bedrooms, number of bathrooms, square footage of the home, square footage of the property, year built and the home condition among other items. The second variable is neighborhood characteristics, which will be captured by the zip codes. Lastly will be the accessibility and location characteristics.

The model takes the following form:

$$V = f(P, N, A)$$

V is the measure of the home's value, and f is the functional form of the three kinds of property attributes: P is physical attributes, N is neighborhood attributes, and A is accessibility attributes. The regression model that is traditionally used is as follows:

$$Y_i = \beta_0 + \beta_1 distance + \beta_2 attributes \ldots + u_i$$

Where Y_i is the sale price of the home in one of the three specified years. $\beta_0$represents the intercept of the sale price. Each subsequent β indicates the effect a given attribute of the house has on the value of that house. This allows us to look at the effect of given attributes on a house's sale price. We build off of this model to conduct a difference-in-differences model to see whether or not the sale prices change due to the construction of the light rail. This study draws on techniques used by Acemoglu, Autor & Lyle (2002) who implement a difference-in-differences model with continuous treatment. The difference-in-differences test will look at three different time changes. First, the test is conducted to analyse the difference between the year 1994 and 2005, testing whether or not there was a change between before and after the announcement of the light rail had occurred. Second, a test is conducted for the years 2005 and 2016, looking to determine the difference between the time after the light rail construction began to the time after the opening of the light rail occurred.

The regression for each of the following tests are as follows:

$$Y_i = \beta_0 + \delta_0\ year + \beta_1 distance + \delta_1 year * distance + \ldots + u_i$$

Where $\delta_0$represents the change in the average house price between 1994 and 2005. This value is obtained by taking the difference in beta values for distance between the year 1994 and 2005. $\beta_1$captures the difference in housing prices between those closer and further away from the light rail stop. Lastly, $\delta_1$illustrates the difference in the prices between those closer and further away from the light rail stop between 1994 and 2005. Included in this regression are the variables stated above that make up the hedonic model. Regressions to compare the other two years are also run, with the dummy for year being 2016 in order to capture the change in price between 2005 and 2016. Lastly, to calculate the ideal distance for each respective year, $distance$^2 and

$year * distance$^2 are created. These values are used to determine the ideal distance away from the light rail stop in 1994, 2005, and 2006.

For the pre-treatment period, the equation to calculate the ideal distance takes the following form:

$$TP_{Pre} = \frac{-distance\ coef}{2(distance\ coeff^{2})}$$

For the post-treatment period, the equation takes the following form:

$$TP_{Post} = \frac{-(distance + (year * distance\ coeff))}{2(distance^{2} + (year * distance\ coeff^{2}))}$$

By adding the year variable, interacting with the *distance* and *distance*^2 variable, this allows us to look at the impact that the light rail has from before construction, during construction, and after completion- giving us the ideal distance for a house to be located away from the light rail in terms of it's appreciation in value. In order to obtain these values, the regression below is utilized.

$$Y_i = \beta_0 + \delta_0\ year + \beta_1 distance + \delta_1 year * distance + \delta_2 distance^2 + \delta_3 year * distance^2 + \beta_2 ZIP5 + \beta_3 PLUS4 + \beta_4 LOTSQFT + \beta_5 Stories + \beta_6 SqFtTotLiving + \beta_7 SqFtGarageAttached + \beta_8 SqFtOpenPorch + \beta_9 SqFtEnclosedPorch + \beta_{10} SqFtDeck + \beta_{11} Bedrooms + \beta_{12} BathHalfCount + \beta_{13} Bath3qtrCount + \beta_{14} BathFullCount + \beta_{15} Condition + u_i$$

Hypothesis:

H_0: $TP_{Pre} = TP_{Post}$

H_{alt}: $TP_{Pre} \neq TP_{Post}$

The null hypothesis states that there is no significant difference, ceteris paribus, in the ideal distance to the Beacon Hill light rail stop between two time periods. The alternative hypothesis states that there is a difference in distances, implying that the light rail has a quantitative impact on housing values in King County.

5. Econometric Results

The two tables below summarize the results from the regressions. Table 3 measures the effect the announcement of the light rail on housing values-utilizing the years 1994 and 2005. Column (1) looks solely at the effect distance and year has on the housing value. Column (2) includes the variables $distance^2$and $year * distance^2$, the variables that are used to calculate the ideal distance. Lastly, column (3) includes all of the hedonic variables to account for both internal and external variables that account for housing value. Table 4 includes the same values and regression coefficients, however it is run with data from 2005 and 2016. The hedonic variables are not included in the results summary for clarity. They can be found in the appendix attached.

Table 3. Regression Results

	Dependent variable:		
	AdjPrice		
	(1)	(2)	(3)
Year	1,771,009.000	2,668,265.000	2,079,190.000
	(228,698.600)	(474,177.800)	(390,058.000)
	p = 0.000***	p = 0.00000***	p = 0.00000***
Distance	-4,103.989	175,117.300	505,582.900
	(280,130.200)	(1,417,018.000)	(1,172,459.000)
	p = 0.989	p = 0.902	p = 0.667
I(Year * Distance)	-1,936,118.000	-6,257,900.000	-5,169,745.000
	(304,522.000)	(1,493,439.000)	(1,229,201.000)
	p = 0.000***	p = 0.00005***	p = 0.00005***
I(Distance2)		-134,457.300	-369,033.600
		(1,048,173.000)	(859,579.200)
		p = 0.899	p = 0.669
I(Year * Distance2)		3,883,409.000	3,292,010.000
		(1,128,051.000)	(928,786.200)
		p = 0.001***	p = 0.001***
Constant	219,248.900	165,013.200	-281,087,920.000
	(211,820.000)	(459,078.200)	(250,384,138.000)
	p = 0.302	p = 0.720	p = 0.264
Observations	200	200	200
R^2	0.621	0.732	0.850
Adjusted R^2	0.615	0.725	0.835
Residual Std. Error	374,960.700 (df = 196)	316,629.600 (df = 194)	245,740.800 (df = 180)
F Statistic	106.850*** (df = 3; 196)	106.081*** (df = 5; 194)	53.822*** (df = 19; 180)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4. Regression Results

	Dependent variable:		
	AdjPrice		
	(1)	(2)	(3)
Year	134,346.800	-4,474,346.000	-3,699,273.000
	(365,901.200)	(817,495.500)	(858,063.100)
	p = 0.714	p = 0.00000***	p = 0.00003***
Distance	-1,940,222.000	-6,082,782.000	-5,175,018.000
	(346,121.100)	(1,529,736.000)	(1,592,158.000)
	p = 0.00000***	p = 0.0001***	p = 0.002***
I(Year * Distance)	273,572.000	18,088,820.000	14,901,214.000
	(536,480.500)	(2,916,341.000)	(2,968,683.000)
	p = 0.611	p = 0.000***	p = 0.00000***
I(Distance2)		3,748,952.000	3,230,937.000
		(1,352,370.000)	(1,378,848.000)
		p = 0.006***	p = 0.020**
I(Year * Distance2)		-14,747,845.000	-12,044,246.000
		(2,391,928.000)	(2,408,001.000)
		p = 0.000***	p = 0.00000***
Constant	1,990,258.000	2,833,278.000	769,855,866.000
	(249,923.500)	(385,047.400)	(609,415,519.000)
	p = 0.000***	p = 0.000***	p = 0.208
Observations	311	311	310
R^2	0.162	0.256	0.347
Adjusted R^2	0.154	0.244	0.304
Residual Std. Error	1,086,784.000 (df = 307)	1,027,027.000 (df = 305)	974,720.500 (df = 290)
F Statistic	19.774*** (df = 3; 307)	21.038*** (df = 5; 305)	8.102*** (df = 19; 290)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3 looks at the difference-in-differences between 1994 and 2005. An important note in the regression is the increase in r-squared with the introduction of the hedonic variables. This illustrates that with all of the variables, the model explains 83% of the variation in the housing prices from 1994 to 2005. This is in contrast to Table 4, which looks at the change from 2005 to 2016. The r-squared for this regression lies just above 30%. This difference implies that the impact of the light rail construction explained much of the change in housing prices in 2005, whereas the actual opening of the light rail does not explain as much of this change. This indicates that there are other factors, such as changes in population density or median income, in effect from the year 2005 to the year 2016. The regressions also provide the necessary values for determining the ideal distance for a property, which is calculated and analyzed below.

1994 & 2005

We utilize the *distance* and *year*distance* coefficients from Table 3 and the equations TP_{Pre} and TP_{Post} in order to determine the ideal distance for a household in 1994 and 2005. The equation to determine the ideal distance in 1994 is as follows:

$$TP_{Pre} = \frac{-distance}{2(distance^2)} = \frac{-505{,}582.9}{-2(369{,}033.6)} = .685$$

This number indicates that in 1994, the ideal distance from the then nonexistent light rail stop at Beacon Hill was .685 miles. We now do the same equation for 2005 to compare the effect that the construction of the light rail has on distance.

$$TP_{Post} = \frac{-(distance + (year * distance))}{2(distance^2 + (year * distance^2))} = \frac{-(505{,}582.9 + (-5{,}169{,}745))}{2(-369{,}033.6 + (3{,}292{,}010))}$$

$$= .797$$

This number indicates that in 2005, the ideal distance from the now under construction light rail stop at Beacon Hill was .797844 miles. The increase in distance implies that the construction of the light rail had a negative effect on the houses closest to the stop, as the ideal distance moved further away. Looking at the *year*distance* and *year*distance2* coefficients in Table 3 explain how moving farther away from the light rail stop affects housing values. The variable *year*distance* is negative and *year*distance2* is positive. This indicates that at first moving away from the light rail stop results in a loss in value, however there is a point in which the house appreciates the further away from the stop it is. This supports the value calculated above because the change from negative to positive indicates that being further away from the light rail stop will have a favorable effect the further away the house is.

2005 & 2016

We now utilize the values from Table 4 in conjunction with the same equations to determine the change in distance from 2005 to 2016.

$$TP_{Pre} = \frac{-distance}{2(distance^2)} = \frac{-(-5{,}175{,}018)}{2(3{,}230{,}937)} = .800854$$

This number indicates that in 2005, the ideal distance from the constructing light rail stop was .800854 miles. It is important to note that the value above and the value from 2005, TP_{Post} are slightly different numbers. This indicates that there may be variations between the two datasets. However, the difference is negligible- it is only .00301 miles or 15.8928 feet. We now do the same equation for 2016 to determine the effect the opening and use of the light rail has on distance.

$$TP_{Post} = \frac{-(distance+(year*distance))}{2(distance^2+(year*distance^2))} = \frac{-(-5{,}175{,}018+(14{,}901{,}204))}{2(3{,}230{,}937+(-12{,}044{,}246))} = .551789$$

This number indicates that in 2016, the ideal distance for a property was .551789 miles from the now operating Beacon Hill light rail stop. This is a significant change from the 2005 distance and indicates that the light rail had a positive impact on properties located closer to the stop, as the ideal distance decreased by roughly .15 miles. Further, this value is less than the 1994 distance, strengthening the hypothesis that the light rail has an overall positive impact on the surrounding housing values. Again looking at the variables at the *year*distance* and *year*distance2* coefficients in Table 4 explain why the coefficient for TP_{Post}, 2016 is lower than that for 2005. The coefficient shifts from positive (*year*distance*) to negative (*year*distance2*). This indicates that after getting too far away from the light rail stop, the value of the house begins to decrease. This helps to explain why the ideal distance in 2016 is closer than that of 2005 and further supports the hypothesis that the implementation of the rail had a positive effect on the property values.

Implications

Since the coefficients of the regressors of interest in Table 4 are significant, and the signs of these coefficients support the change in distance from TP_{Pre} to TP_{Post}, we can reject the null hypothesis that the opening of the light rail had no effect on the properties within a one-mile radius of the Beacon Hill stop. However, the lack of significance in the coefficients for *distance* and *distance2* in Table 3 indicates that we cannot with certainty reject the null hypothesis that the construction of the light rail had a significant impact on ideal distance for properties from 1994 to 2005.

In all, the paper indicates that the opening of the light rail at Beacon Hill does lead to a shift in ideal distance for properties located within a one-mile radius. With high expected expansion in the Seattle area, this finding implicates how other stations and the expansion of the LINK may affect other neighborhoods in King County. However, the implication that each station has this effect in their respective location requires further examination, as this study only tests a single stop on the LINK line.

Further, the values of the coefficients utilized while calculating ideal distance are fairly large. A one foot increase in distance away from the light rail correlates to a $2,822.20 increase in housing value, utilizing the *distance*year* value from Table 4. Regardless of the significance level, this is incredibly large and may point to a flaw in the data utilized. The lack of precise data for the county is a limitation that this study encounters. Additions of area code specific data regarding employment levels and median income would make this analysis more robust and build a stronger hedonic model for measurement. Unfortunately, this data was not available for the specified years and has potential impacts on the regressions.

Lastly, it should be noted that this data should not be extrapolated to other cities, as the reviewed literature suggests each metropolitan area is unique and subject to a unique set of significant variables. Though the analysis does offer results in support of the hypothesis that the light rail stop affects ideal distance for properties, the data available does not provide sufficient variables in order to build a robust hedonic model. Further additions to the analysis and expansion of the studied area are necessary in order to determine the true effect of the light rail on the entirety of the line.

Conclusion

This study finds data to suggest that the opening of the LINK light rail station at Beacon Hill had a measurable impact on properties in the surrounding area. However, a number of data restrictions limit the strength of the hedonic model. This indicates that a more robust data collection is necessary in order to gain a stronger understanding of the light rail effect. Further, extension of the studied field to encompass each light rail stop will help build a stronger comprehension of the impact that the rail has in King County. Including items such as average income, job availability, and population density would help build a much stronger hedonic model and further add significance to the impact that the rail has. The study elucidates the necessity for further research and brings to light the impact the the light rail has at different stages of its development. With the rise of population in Seattle and no signs of that growth slowing down, there are many reasons to look further into the way in which the LINK light rail and other forms of transportation affect properties in King County.

Appendix

Table 3. Regression Results

	Dependent variable:		
	AdjPrice		
	(1)	(2)	(3)
Year	1,771,009.000	2,668,265.000	2,079,190.000
	(228,698.600)	(474,177.800)	(390,058.000)
	p = 0.000***	p = 0.00000***	p = 0.00000***
Distance	-4,103.989	175,117.300	505,582.900
	(280,130.200)	(1,417,018.000)	(1,172,459.000)
	p = 0.989	p = 0.902	p = 0.667
I(Year * Distance)	-1,936,118.000	-6,257,900.000	-5,169,745.000
	(304,522.000)	(1,493,439.000)	(1,229,201.000)
	p = 0.000***	p = 0.00005***	p = 0.00005***
I(Distance2)		-134,457.300	-369,033.600
		(1,048,173.000)	(859,579.200)
		p = 0.899	p = 0.669
I(Year * Distance2)		3,883,409.000	3,292,010.000
		(1,128,051.000)	(928,786.200)
		p = 0.001***	p = 0.001***
ZIP5			2,862.707
			(2,551.116)
			p = 0.264
PLUS4			34.354
			(25.462)
			p = 0.179
LOTSQFT			-2.537
			(0.887)
			p = 0.005***
Stories			3,432.262
			(64,746.810)
			p = 0.958
SqFtTotLiving			108.464
			(42.508)
			p = 0.012**
SqFtGarageAttached			500.429

			(91.008)
			p = 0.00000***
SqFtOpenPorch			577.441
			(186.302)
			p = 0.003***
SqFtEnclosedPorch			711.572
			(491.049)
			p = 0.150
SqFtDeck			74.084
			(141.370)
			p = 0.601
Bedrooms			-40,429.920
			(30,086.260)
			p = 0.181
BathHalfCount			-137,049.300
			(48,322.540)
			p = 0.006***
Bath3qtrCount			-52,944.420
			(50,520.710)
			p = 0.297
BathFullCount			41,524.040
			(52,772.450)
			p = 0.433
Condition			6,240.297
			(43,154.900)
			p = 0.886
Constant	219,248.900	165,013.200	-281,087,920.000
	(211,820.000)	(459,078.200)	(250,384,138.000)
	p = 0.302	p = 0.720	p = 0.264
Observations	200	200	200
R^2	0.621	0.732	0.850
Adjusted R^2	0.615	0.725	0.835
Residual Std. Error	374,960.700 (df = 196)	316,629.600 (df = 194)	245,740.800 (df = 180)
F Statistic	106.850*** (df = 3; 196)	106.081*** (df = 5; 194)	53.822*** (df = 19; 180)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4. Regression Results

	Dependent variable:		
	AdjPrice		
	(1)	(2)	(3)
Year	134,346.800	-4,474,346.000	-3,699,273.000
	(365,901.200)	(817,495.500)	(858,063.100)
	p = 0.714	p = 0.00000***	p = 0.00003***
Distance	-1,940,222.000	-6,082,782.000	-5,175,018.000
	(346,121.100)	(1,529,736.000)	(1,592,158.000)
	p = 0.00000***	p = 0.0001***	p = 0.002***
I(Year * Distance)	273,572.000	18,088,820.000	14,901,214.000
	(536,480.500)	(2,916,341.000)	(2,968,683.000)
	p = 0.611	p = 0.000***	p = 0.00000***
I(Distance2)		3,748,952.000	3,230,937.000
		(1,352,370.000)	(1,378,848.000)
		p = 0.006***	p = 0.020**
I(Year * Distance2)		-14,747,845.000	-12,044,246.000
		(2,391,928.000)	(2,408,001.000)
		p = 0.000***	p = 0.00000***
ZIP5			-7,818.083
			(6,211.456)
			p = 0.210
PLUS4			-105.307
			(58.666)
			p = 0.074*
LOTSQFT			-3.784
			(2.819)
			p = 0.181
Stories			170,736.100
			(218,065.100)
			p = 0.435
SqFtTotLiving			124.457
			(131.901)
			p = 0.347
SqFtGarageAttached			367.459

			(272.481)
			p = 0.179
SqFtOpenPorch			1,188.484
			(541.579)
			p = 0.029**
SqFtEnclosedPorch			815.576
			(1,809.663)
			p = 0.653
SqFtDeck			-265.204
			(459.168)
			p = 0.564
Bedrooms			25,991.440
			(90,804.710)
			p = 0.775
BathHalfCount			-240,729.300
			(171,988.600)
			p = 0.163
Bath3qtrCount			-175,186.200
			(161,734.000)
			p = 0.280
BathFullCount			-140,740.000
			(165,889.900)
			p = 0.397
Condition			-167,355.600
			(133,065.800)
			p = 0.210
Constant	1,990,258.000	2,833,278.000	769,855,866.000
	(249,923.500)	(385,047.400)	(609,415,519.000)
	p = 0.000***	p = 0.000***	p = 0.208
Observations	311	311	310
R^2	0.162	0.256	0.347
Adjusted R^2	0.154	0.244	0.304
Residual Std. Error	1,086,784.000 (df = 307)	1,027,027.000 (df = 305)	974,720.500 (df = 290)
F Statistic	19.774*** (df = 3; 307)	21.038*** (df = 5; 305)	8.102*** (df = 19; 290)
Note:			*p<0.1; **p<0.05; ***p<0.01

Works Cited

Acemoglu, D., Autor, D. H., & Lyle, D. (2004). Women, war, and wages: The effect of female labor supply on the wage structure at midcentury. *Journal of political Economy*, *112*(3), 497-551.

Bhatta, S. D., & Drennan, M. P. (2003). The economic benefits of public investment in transportation: A review of recent literature. *Journal of Planning Education and Research*, *22*(3), 288-296.

Bowes, David R, & Ihlanfeldt, Keith R. (2001). Identifying the Impacts of Rail Transit Stations on Residential Property Values. *Journal of Urban Economics.*, *50*(1), 1-25.

Chatman, D. G., Tulach, N. K., & Kim, K. (2012). Evaluating the economic impacts of light rail by measuring home appreciation: A first look at new jersey's river line. *Urban Studies*, *49*(3), 467-487.

Dorantes, L. M., Paez, A., & Vassallo, J. M. (2011). Analysis of house prices to assess economic impacts of new public transport infrastructure: Madrid metro line 12. *Transportation Research Record*, *2245*(1), 131-139.

Garber, A. (2001, September). Light rail lite goes to vote tomorrow; 1st leg would link Seattle, Tukwila. Retrieved from https://archive.seattletimes.com/archive/?date=20010926&slug=sound26m.

Guy, G. B. / F. Y. I. (2018, May 24). 114,000 more people: Seattle now decade's fastest-growing big city in all of U.S. Retrieved from https://www.seattletimes.com/seattle-news/data/114000-more-people-seattle-now-this-decades-fastest-growing-big-city-in-all-of-united-states/.

Hopkins, E. A. (2018). The influence of public transportation on housing values. *International Journal of Sustainable Development & World Ecology*, *25*(3), 206-215.

King County Department of Assessments. (n.d.). Retrieved from https://info.kingcounty.gov/assessor/DataDownload/default.aspx.

Liou, F., Yang, S., Chen, B., & Hsieh, W. (2016). The effects of mass rapid transit station on the house prices in taipei: The hierarchical linear model of individual growth. *Pacific Rim Property Research Journal, 22*(1), 3-16. doi:10.1080/14445921.2016.1158938

Martínez, L. M., & Viegas, J. M. (2009b). Effects of transportation accessibility on residential property values: Hedonic price model in the lisbon, portugal, metropolitan area. *Transportation Research Record, 2115*(1), 127-137.

Pan, Q. (2013). The impacts of an urban light rail system on residential property values: A case study of the houston METRORail transit line. *Transportation Planning and Technology, 36*(2), 145-169. doi:10.1080/03081060.2012.739311

Pryne, E. (2002, March). Sound Transit gets green light to buy land for light rail. Retrieved from https://archive.seattletimes.com/archive/?date=20020315&slug=sound15m.

Yardley, W. (2016, April 4)On the Ground: Seattle continues quest to get greener as it grows with 'transformative' light-rail expansion. Retrieved from https://www.latimes.com/nation/la-na-sej-seattle-light-rail-20160404-story.html.

Yu, H., Zhang, M., & Pang, H. (2017). Evaluation of transit proximity effects on residential land prices: An empirical study in austin, texas. *Transportation Planning and Technology, 40*(8), 841-854. doi:10.1080/03081060.2017.1355880

68% of the world population projected to live in urban areas by 2050, says UN | UN DESA Department of Economic and Social Affairs. (2018). Retrieved from https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html