The Impact of Hudson-Bergen Light Rail on Residential Property Appreciation

Keyongsu Kim[1] and *Michael Lahr*[2]

April 17, 2012

Abstract. This paper analyzes the impact of the Hudson-Bergen Light Rail (hereafter HBLR) on residential property prices. Unlike similar studies that use a hedonic model with cross-sectional data, this one uses repeat-sales data of properties that sold at least twice between 1991 and 2009. It shows how proximity to the nearest HBLR station, relative accessibility gains across stations, and the commencement date of the HBLR station influence home price change. Our results show that properties near the two commuting stations farthest from the revitalized CBD experienced high appreciation. It also reveals that different accessibility gains across areas were produced based on the availability of existing public transportation options. Using a negative–exponential gradient, we find that these higher appreciation rates tended to dissipate about 1/4 mile (402 m) from stations. This supports that properties around urban commuting stations enjoy higher marginal benefits through improved transit accessibility and reduced transportation costs as Alonso's model predicts.

Introduction

Even before the Hudson-Bergen Light Rail line (HBLR) began operation in 2000, a debate was underway in the U.S. that weighed in on the advantages and disadvantages of investment in light rail systems. Listed advantages were reduced pollution, congestion, and energy consumption levels along with more compact economic development. The prime disadvantage was the size of annual government subsidies required to underwrite such projects that appeared to benefit a relative few. Nevertheless, rising environmental awareness, sky-rocketing real prices of gasoline and diesel fuel, local bonds, and federal and state transportation capital funding enabled several new light rail transits (LRT) in the U.S. Admittedly, enhancing economic development around light-rail stations was another substantial bullet point to booster LRT (Garrett, 2004). METRORail in Houston, Hiawatha light rail in Minneapolis, Lynx in Charlotte RiverLine in southern New Jersey connecting Trenton and Camden, and HBLR, for example,

[1] The Louis Berger Group, Inc, 199 Water Street, 23rd fl., New York, NY 10038. email: kim@louisberger.com Tel: 1.212.383.7233 7 Fax: 1.212.383.2418.

[2] Rutgers Economic Advisory Service, Rutgers University, 33 Livingston Avenue, New Bruynswick, NJ 08901-1982. Email: lahr @rutgers.edu

were planned and opened during an LRT revival.

Despite the surge in new LRT facilities, naysayers did not let up. They subsequently pointed to higher-than-expected construction costs, low ridership, and the slow progress of development near LRT stations. Supporters noted that LRT is believed to be a more sustainable transportation option vis-à-vis highway-oriented infrastructure investment; and economic development near transit stations was never expected to be quick. Both groups agree, however, that one aspect of economic development should be fairly fast, i.e., residential properties near transit stations should appreciate in value. This is because they should capitalize immediately on their new-found accessibility, perhaps even speculatively, before the transportation investment operates. The Alonso–Wingo model, purported by planners and developers alike, suggests when transit lowers commuting costs property values should rise throughout transit's urban reach. The underlying assumption for higher property values is that rail system must reduce commuting costs, either in the form of perceived total transit time or monetary costs.

In the wake of Alonso's 1964 book, many studies were undertaken, valuating properties along new commuter and heavy rails. A few studies have found mixed, no, or negative impacts on property values of rail transit (Dornbush, 1975; Armstrong, 1994; Bowes and Ihlanfeldt, 2001). Yet, they generally found that properties proximate to the rail stations owned a property value premium (Graybeal and Gifford, 1968; Boyce, 1972; Lee, 1973; Dewees, 1976; Damm et al, 1980; Baijic, 1983). Some recognized that businesses are even more likely to enjoy the accessibility gain than households (Weinstein and Clower, 1999; Cervero and Duncan, 2002 Debrezion G et al, 2007). These findings were no real surprise, for historically rail had altered both the nature of urban systems and the internal structural form of cities from its infancy (Jackson, 1985; Xie and Levinson, 2010). Admittedly, accessibility gains cannot be identical among different rail types (i.e., commuter rail, subway, light rail, and others) due to dissimilar magnitude of their accessibilities. Relatively lower speeds realized by LRT service compared to other forms of commuting are expected to result in lower rates of appreciation for residential properties than obtained via other forms of transportation. Still, home price rises are expected.

When it comes to property appreciation, it is clear that multifarious factors, not just rail alone, are involved. Land use controls and economic growth independent of the rail network can influence land-market responses (Knight and Trygg, 1977). Over time, therefore, the burgeoning literature on housing hedonics has attempted to valuate or control for many items that could affect properties' values such as tax payments; proximity to recreational amenities, quality schools, retail establishments, and churches; and even proximity to "bads" such as nuclear electricity generation stations, brownfields, and superfund sites. As early as Graybeal and Gifford (1968), analysts formally recognized in hedonic analysis that highways and automobiles combined are after all a prime competitor to rail, so that properties can also capitalize on accessibility enabled by them (Voith, 1993). Admittedly, being too close to a major road also can engage some negative externalities. In general, however, the increasing density of U.S. highway networks has lowered the marginal value of accessibility through reduced road transportation costs (Fernald, 1999). Indeed, the marginal value has been asymptotically approaching negligible levels (Giuliano 1989; Glaeser and Kohlhase, 2004). Consequently, as the density of highways has increased, the value of moves (relocations) for each household to exploit transportation cost reduction has declined, perhaps to the point that it no longer overcomes the friction of moving to improve workplace accessibility alone.

In light of the capitalization impact from new LRT investment, Hudson County, New Jersey may be an ideal setting to evaluate the ability of properties to capitalize on their proximities to a light rail station. First, the road network in Hudson County was largely built decades ago: and only minor repairs and realignments have been made since plans for the HBLR were announced. Hence, the effect of highway accessibility on recent property prices should be negligible. Insofar as accessibility's impact on property prices is concerned, then, only recent transit investment (opened since about 2000) should reveal itself as important. Second, HBLR provides a new public transportation link to Jersey City's newly developed waterfront central business district (hereafter, JCCBD waterfront), where direct transit connections exist between New Jersey and New York City (NYC) as well. Thus, according to the Alonso-Wingo model, new accessibility gains due to the presence of the HBLR should raise bid-rents around HBLR stations. In particular, the price effect is likely to be greatest (for a fixed quantity of property) as properties distant from the CBD (figure 1 demonstrates this relationship). In reality, however, the accessibility gain cannot simply be justified by distance. An actual accessibility is not justified by distance but rather by net gains in transit time for residents' everyday trips. Regardless, people who prefer the HBLR to other forms of travel should want to live close to its transit stops. In this vein, Alonso-Wingo theory suggests these transit-preferring residents will pay a premium for this prospect up to some amount less than the life-time savings (in terms of actual transportation expenses and the opportunity value of their time) that they will enjoy at the location. Thus, the HBLR is likely to be capitalized in the real estate market.

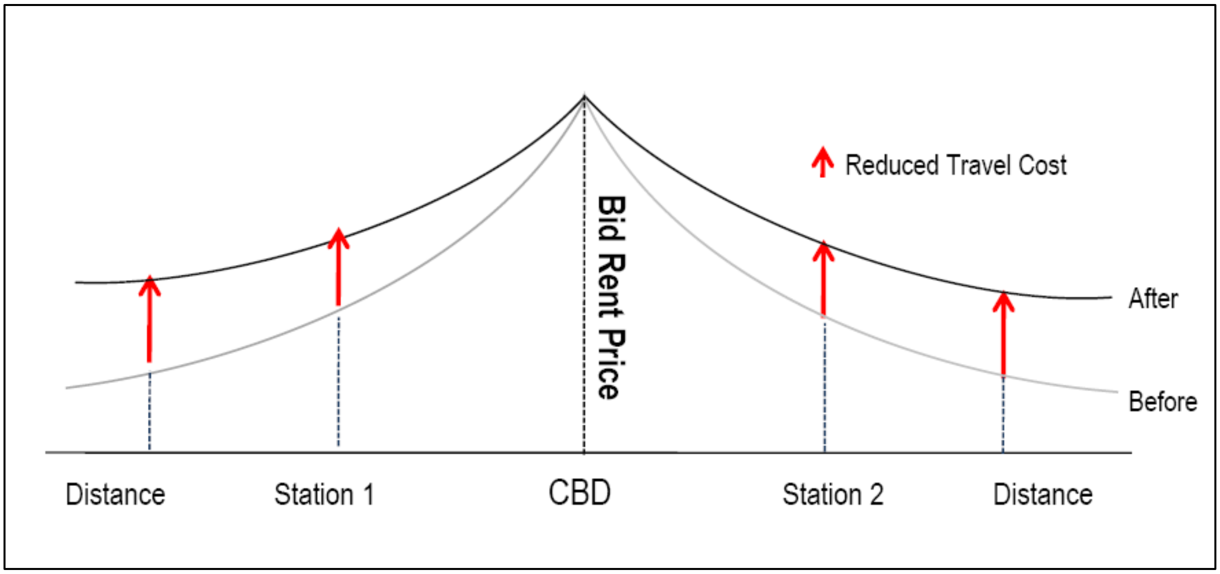

Figure 1 Effect of Reduced Transportation Costs on Property Values

In this paper we strictly report the effect of the HBLR that has had on residential (one to four units) properties sold at least twice between 1991 and 2009. We initially assumed that properties near three HBLR stations (called urban commuting stations here) farthest from the JCCBD waterfront gain the greatest benefits. That is, we realized the relative magnitude of accessibility gains will be different throughout the HBLR service areas due to dissimilar existing public transportation options as well as dissimilarities in the percentage change due to improved accessibility. In particular, northern part of Hudson County, which has good bus connections to Manhattan (the regional job hub), is expected to experience lower service gains than will other areas of the county. Thus, we hypothesized that net accessibility gains are not only likely to be higher when costs are reduced due to longer distances traveled but also when existing public transportation options are less abundant. Hence, we tested how the impacts of the HBLR differ by station. Because the analysis is performed on price changes between the first and second (most recent) sales at any time during the period, we also investigate multiple ways to put the sales prices into constant (real) monetary terms.

In the following section we describe the HBLR's progressive development, current ridership trends, pre-HBLR accessibility, and socio-demographic characteristics of HBLR service areas. We believe this all helps the reader understand the magnitude of relative accessibility gains made possible by the HBLR. We then review the literature on the effect of LRT on property values, to further develop research hypotheses already briefly touched upon. This is followed by a discussion of the study dataset and approach used to perform the analysis. A section presenting and discussing our findings follows, including comparative analyses to prior studies. We conclude with a summary of findings, policy implication for LRT and suggestions for further research.

Description of the HBLR and Its Service Area

As planned in 1984, the HBLR was to regenerate Hudson County's economy by improving transit accessibility in which the highway and street network had dominated. The $2.2 billion LRT project was executed in 1996 with a design/build/operate/maintain contract via a public and private partnership that was forged between the Washington Group International and New Jersey Transit. The first phase of a 9.5 mile (15.2 km) segment extended from Exchange Place south as far as to 34th Street in Bayonne and southwest to West Side Avenue in Jersey City in 2000 (two lines share a track between a Liberty State Park station and Newport station in Jersey City; see the figure 2). Extensions northward to the waterfront at Newport station followed in 2001, and another north to NJ Transit's Hoboken Terminal in 2002. In 2003, the line extended south to 22nd Street in Bayonne. The following year, it extended even farther northward to Lincoln Harbor in Weehawken. Port Imperial in Weehawken, Bergenline Avenue in Union City, and Tonnelle Avenue in North Bergen were added in 2006. The most recent extension was completed in 2011, adding 8th Ave in Bayonne. As of January 2011, the HBLR is 20.6 miles (33.2 km) long and serves seven municipalities via 24 stations along the Hudson River waterfront as figure 2 shows. Today, the HBLR operates as a "proof-of-payment" fare collection system. A $100 fine is applied for failure to show a ticket upon official request. A one-way adult fare is $2.10 and unlimited monthly pass is $64. The HBLR shuts down daily on from 2 AM to 5 AM. It has peak headways of about 5 minutes but they are relaxed to as much as 10 minutes during off-peak hours. During peak hours, occasional express train service operates between Bayonne and Hoboken Terminal.

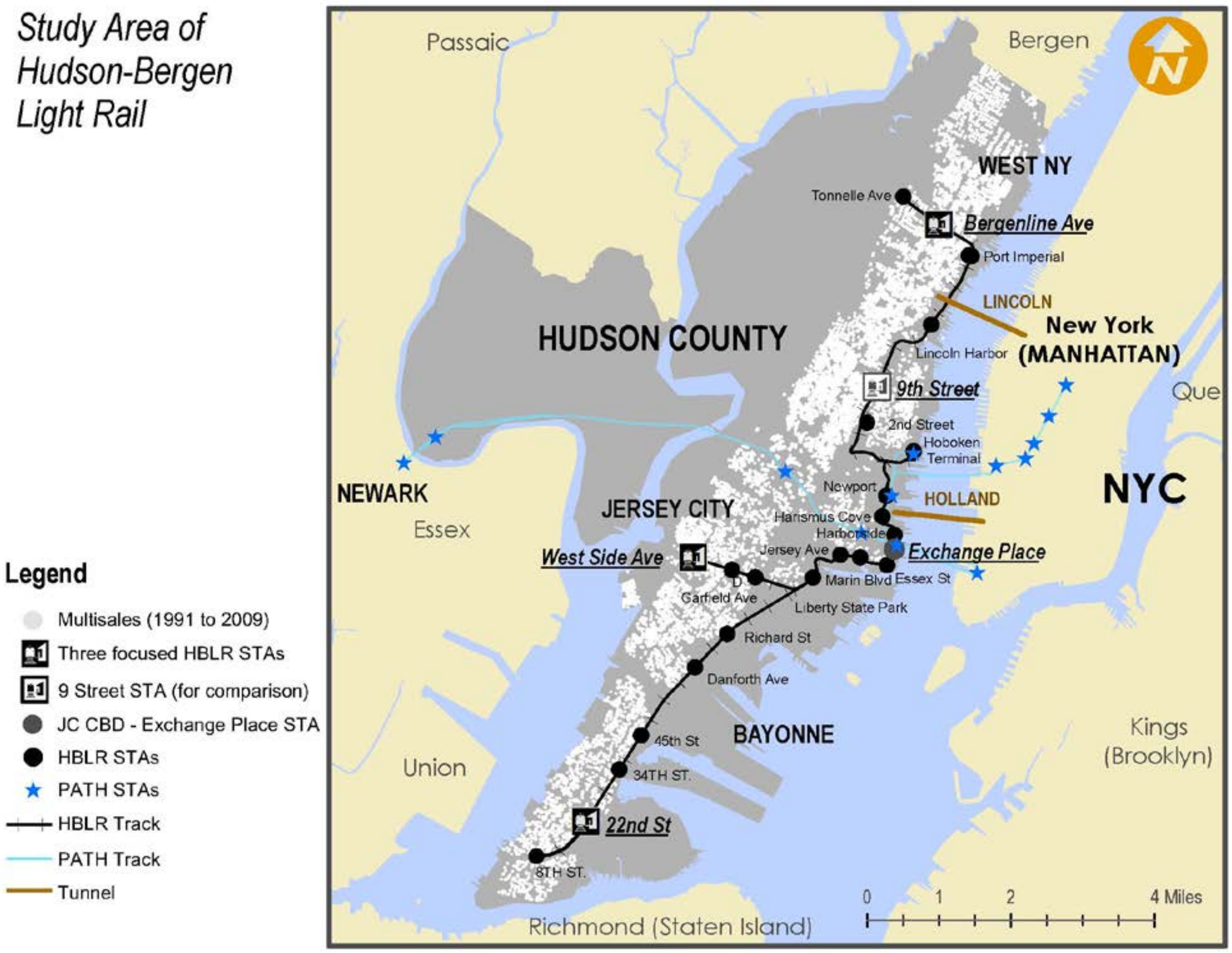

Figure 2 Study Areas (Seven Municipalities along HBLR)

Table 1 presents the average daily boardings since its inception. Newport, Hoboken, Exchange Place, and Harborside stations are defined here as within the JCCBD waterfront, where a professional and financial industry cluster developed starting in the 1980s, due in part to fairly direct access to both Downtown and Midtown Manhattan through the Port Authority Trans-Hudson (PATH) train. It also includes one outlier station – Liberty State Park. This station is essentially a feeder for a tourist venue. It is home of a science museum largely visited by student groups, yields access to Ellis Island, and is base of operation for ferries that run to the Statue of Liberty. Also, of the generous parking at the station make it a natural HBLR collection point for CBD and Manhattan workers who live southwest of the county. The stations that follow represent extreme ends of the HBLR: Bergenline Ave, West Side Avenue, 22nd Street and 34th Street.

Table 1 HBLR Daily Average Boardings since its Operation to 2009

2008 Ranks	Stations	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	Newport		411	2,725	2,885	2,625	2,997	3,256	4,825	5,447	5,824
2	Hoboken				1,931	2,391	3,710	4,707	5,048	5,381	5,830
3	Exchange Place	1,453	2,302	2,641	2,806	2,584	2,853	3,092	4,196	4,830	4,997
4	Bergenline Avenue							1,413	2,125	2,641	2,872
5	Liberty State Park*	618	1,390	2,048	2,071	1,852	1,913	1,808	2,450	2,725	2,771
6	9th Street						620	923	1,812	2,193	2,427
7	22nd Street*					468	1,141	1,313	1,748	1,811	1,995
8	West Side Avenue*	204	368	613	771	711	870	931	1,342	1,634	1,693
9	34th Street*	638	935	1,266	1,211	955	907	948	1,236	1,495	1,720
10	Harborside		338	958	1,363	1,142	1,219	1,222	1,609	1,726	1,801
11	Essex Street	68	107	499	915	665	763	766	991	1,153	1,159
12	MLK Drive	109	233	408	444	464	612	640	882	1,037	1,109
13	Tonnelle Avenue*							608	873	995	1,071
14	Harsimus		61	195	285	330	453	519	756	793	918
15	2nd Street						196	325	739	854	924
16	Port Imperial							417	618	784	840
17	Jersey Avenue	56	113	139	146	184	390	409	610	698	810
18	45th Street	291	449	557	500	496	611	607	804	824	903
19	Danforth Avenue	135	223	331	350	372	480	483	657	719	773
20	Lincoln Harbor						305	491	821	890	878
21	Garfield Avenue	58	120	190	222	237	328	380	491	589	684
22	Richard Street	71	131	232	234	274	345	336	439	499	552
23	Marin Boulevard	99	169	248	266	350	337	256	328	382	449
	All Stations	3,800	7,350	13,050	16,400	16,100	21,050	25,850	35,400	40,100	43,000

Source: NJ Transit
* Parking lot is available.

The municipalities served via HBLR have rather diverse local characteristics. Distinct socioeconomic and -demographic characteristics and dissimilar existing accessibility with public transportation may influence a HBLR ridership propensity; thereby, produce different accessibility gains capitalized in property value. To better recognize these local circumstances, three political and demographic groups can roughly be categorized: Jersey City/Hoboken, Bayonne, and the cluster of northern municipalities. Like other Rustbelt cities, Jersey City experienced decline during the early 1960s. Since the 1990s, new commercial/office building and luxury residential developments in the JCCBD waterfront (near PATH stations; Pavonia-Newport and Exchange Place) have occurred; there, residential property prices have been buoyed by their accessibility to Manhattan. Areas beyond walking-distance to PATH stations have yet to partake in this revival, however. Investment in the HBLR was intended to stimulate the local economy by enhancing accessibility to the JCCBD waterfront, particularly areas the county's low-income neighborhoods that retain high shares of minority populations.

Hoboken is unique in the region because of its geographic and a long-established transportation link to Manhattan. The Lincoln Tunnel, PATH, and ferries make that connection. Historically its well-preserved urban ambience with brownstone and bricks residential buildings, a variety of retail stores, and numerous restaurants and bars have made Hoboken an attractive residential community for Manhattan-based workers. Young professionals without school-aged children who seek ready access to Manhattan's many amenities but at a lower housing price are particularly attracted to the city.

Bayonne, located at the southern end of Hudson County's peninsula, was a home to a set of vibrant refineries, a port and rail yards prior to World War II. Yet, it ceased to be an attractive location for business and residence even before a major naval terminal closed in 1995. Due to its geographical isolation, transit accessibility to Manhattan prior to the HBLR had almost always been inferior to that available to the northern part of the county. According to U.S. Census Bureau's 2005-2009 American Community Survey (ACS) 5-Year Estimates, Bayonne has the county's highest share of senior population (14.2%) while it also retained Hudson County's lowest share of working-age population (61.3%).

Finally, the northern municipality cluster includes Union City, North Bergen, and West New York, all of which have been immigrant communities since their foundation. The cluster is composed of neighborhoods with high percentages of foreign-born (mostly Hispanic) populations and high shares of low income households.. Yet, it has easy access to the Port Authority Bus Terminal (PABT) in Midtown Manhattan, thanks to the Lincoln Tunnel, which maintains designated bus lanes during peak hours. Hence, this area's accessibility gains from the added presence of the HBLR may be lower than it is in other areas of the county where public transportation options were more limited prior to the HBLR.

Literature Review and Research Hypotheses

A large literature has formed on the effect of commuter and intercity rail on property values. Much of it has been reviewed and summarized by various researchers (Knight and Trigg, 1977; Huang, 1996; Ryan, 1999; Bartholomew and Ewing, 2011). Ryan (1999) tells future researchers that, thanks to improved accessibility, property value changes tend only to be captured when travel time savings to existing commercial centers are present and are accurately measured. For this reason, she underlines the importance of connecting new track to existing commercial centers. Ultimately, her point is that urban redevelopment can still be transit-oriented but it seems to have fairly well-defined spatial limits, especially when dealing with rail.

While studies of commuter rail in general are relatively abundant on an international scale, those of light rail are more limited in quantity. This is partly because many light rail systems had been put in place since the first third of the 20th century. Interest in light rail has renewed. Indeed, it is riding a wave of enthusiasm in the U.S. akin to the subway/ commuter rail boomlet of the early 1970s that brought MARTA to Atlanta, BART to the Bay Area, and the Metro to Washington, D.C. The single thing that separates the current light-rail boom from the subway-building era of the 1970s is that transit systems are now being designed not only to move commuters but to drive and shape urban (re)development. This underlines the importance of properly evaluating the effect of these systems on land values and the change in land uses near them.

The City of San Diego launched the first modern light-rail line in 1981 in the U.S. But it was only after Portland, Oregon, demonstrated how light rail could drive development patterns and after Dallas showed that trains in less densely urbanized urban areas could attract solid ridership. Since these early efforts, more cities decided to seek systems of their own and the following light rail have been evaluated: Metro of Buffalo, Metro of Houston, Hiawatha light rail in Minnesota, Lynx in Charlotte and DART in Dallas. To estimate the capacity of housing to capitalize on proximity to transit, most researchers have examined various characteristics of the property and of the neighborhood that correlate with property prices. A key set of variables related to the property is that relating to its proximity to the LRT and competing modes of transportation. The following subsections detail some theory and hypotheses behind variables of interest to the present study.

Hedonic Distance Effects

In general, studies show that proximity to LRT stations tends to be more influential on property value than any other characteristics of the properties or their neighborhoods. In essence, the findings have been similar to those for commuter rail and recently débuted bus rapid transit

(BRT). A key manner in which studies differ is the way they estimate rent surfaces near transit stations. Two basic approaches have been employed: one estimates the average premium that properties that accrue to properties within some pre-specified distance of transit stations and the other estimates a property value gradient for properties that results from their relative proximities to transit stations. In both cases, various distances between 0.25 miles (0.4 kilometer) to 1.25 miles (2.0 kilometers) have been used.

When an average premium is estimated, the size of the pre-defined study area, a so-called "buffer boundary," can affect the magnitude of effects obtained (Dowall, 1980). If the distance selected is larger than it actually is, estimates that result are downwardly biased; on the other hand, they are biased upwardly when the distance selected is smaller than it actually is. Hence, in evaluating the same station for the same transit line, two researchers could easily conclude differently about the magnitude of transit capitalization by properties. The inability to obtain such bias lends the gradient approach greater appeal. The approach also adheres more closely to Alonso-Wingo theory. In fact, armed with gradients and estimates of capitalized values immediate to the stations, one could measure the aggregate capitalization premium over the entire service area of an LRT. To do so, however, one must assume that the gradient is the same in all directions around each given station and that it diminishes to no less than a zero value. Of course, Alonso-Wingo theory suggest such an assumption may not be so idealistic since the cost of transport to stations --in this case walking-- should be the same across stations. That said, this theory also asserts less realistically that all commuters have the same preference set.

Very few studies of property values near LRT lines have opted to use the gradient approach (Chen, Rufolo, and Dueker, 1998; Hess and Almeida, 2007; Goetz et al, 2008). These teams of researchers have tended to estimate nonlinear gradients with quadratic terms rather than the negative exponential gradient, typically used in urban analysis of related concepts (Manson, 1981; Breuckner, 1982). Quadratic functions, however, can undoubtedly approximate the negative exponential distribution within the range of distances examined. By leaning on Li and Brown (1980), Chen, Rufolo, and Dueker (1998) rationalized using something other than a negative exponential decay function. Their implicit point for property values near LRT lines is that the LRTs themselves could increase the production of public *bads* in the form of noise, transient traffic of pedestrians unknown in the neighborhood, and loitering near LRT stations. Thus, they hypothesized that property values very near LRT lines as well as stations are likely to be depressed compared to those distant from the line or station. Despite the interesting hypothesis, Chen, Rufolo, and Dueker (1998) failed to find any nuisance effects related to stations. They did detect nuisance effects elsewhere along the Portland's MAX line, however. To date all research on the topic of LRTs has tended to adopt the rather strong assumption that the gradient across stations is the same, which is unlikely to be a case due to dissimilar cost savings across stations as suggested by Figure 1.

Neighborhood Characteristics

As important to the value of a property as its own quantity and quality, is the perceived value of neighboring properties. Using this as a basic rationale, many hedonic studies have included the neighborhood's median household income or median home value. Higher values of these factors are hypothesized to affect property values in a positive manner. Similarly, district-average student scores on national or state standardized tests have been applied to control for school quality, since schools are the main local public good provided. To account for discrimination on the part of home buyers (and perhaps sales agents as well), hedonic models have also controlled for many neighborhood attributes of households including share that have minority heads, that are headed by women, that are not fluent in English, and that are foreign born. To control for a different housing segment, some models have also controlled for the share of homes in the neighborhood that are rented as opposed to being owner-occupied. In all cases, property prices are hypothesized to be lower in the presence of such factors.

Data Description and Formulation of the Regressand

State of New Jersey's property sales records are publicly available. Bailey, Muth, and Nourse (1963) first applied the repeat sales approach using sales record data, although McMillen and McDonald (2003) and Chatman, Tulach and Kim (2012) have applied it more recently. The advantage of this approach is to examine the actual object of analyses – property price appreciation – rather than infers it from cross-sectional or pooled cross-sectional analyses of sales prices or assessed values, which is what the large body of literature on transit capitalization has leaned upon.

In essence, the basic theoretical model to measure repeat sales should look as follows:

$$\Delta P^h = P_2^h - P_1^h = \sum_i ((P_{i2}\Delta Q_i) + (\Delta P_i Q_{i1})) \qquad (1)$$

$\Delta P^h = P_2^h - P_1^h$ is the change in the property value where P_1^h and P_2^h are property values in time 1 and 2 respectively. The P_{i2} is the price of each attribute i in time 2 and ΔP_i are the price changes of those attributes between time 1 and time 2; Q_{i1} is the quantity of attribute i in time 1 and ΔQ_i is the change in the quantity of attribute i. That is, the change of a property value is the sum of two sets of basic measurements: the total value of any new attributes (or changes in existing ones) and the change in value of existing attributes.

New Jersey's public property sales records are not without problems, however. They lack details on the attributes of recorded properties: at best, beyond location identifiers, they include information of lot size and year the primary structure was built. Thus, it is impossible to estimate the price change in all attributes tht the theoretical model requires. Contrary to Goetzmann and Spiegel's (1995) conjectures, this level of data omission may not be so damning, The work of Coulson and Lahr (2005) on older neighborhoods of Memphis suggests that few variables on changes in attributes affect assessed property values at least over a four-year period. Indeed, they included variables on changes only for the number of bedrooms and bathrooms, despite having at their disposal a full array of variables for their analysis. Hence, we rely strongly on Wang and Zorn's (1997) notion that a major advantage of the repeat sales approach is that researchers can ***largely*** avoid specifying critical characteristics that determine a property's value.

As mentioned earlier, we want to measure how the presence of the HBLR influenced property price change. The ratio of values between two sales events is our main interest. Clearly, however, there are some issues in measuring this ratio given that the value of money differs over time. Also, housing markets are both segmented and cyclic. In the related empirical literature, using a price index to control for relative prices has rarely been a concern since the typical analysis has tended to use cross-sections, cross-sections paired across just two points in time, or unrelated cross-sections pooled over many periods; none of which require explicit control for relative prices over time. Besides, if the two sets of house sales are reported for the same years across all observations, concerns about general inflation and housing market cycles need not come into play, especially in the case of small geographic areas. This was the case for the work on assessed values performed by Coulson and Lahr (2005). In this vein, the use of repeat sales data makes matters more complex, for such sales do not occur in a regular pattern across time. Successive sales of an observed property could more or less occur any time during that period. Bearing this in mind, we tested three different dependent variables that convert the sales prices into a constant-value form.

For the first alternative, we used the ratio of the two sales; both adjusted to 2009 monetary terms using the housing component of CPI-U, which is typically practiced in a pooled cross-session analysis, for New York metropolitan area[3]. Using the metro-wide price-adjusted ratio, we also estimated the *annual* average appreciation rate as the second alternative. This latter additionally controls for the time that transpired between the two sales, which we believed would make it superior. The following are the formulae we used.

$$\frac{\text{CPI}-\text{adjusted Sales Price in the Last Yr}}{\text{CPI}-\text{adjusted Sales Price in the First Yr}} \tag{2}$$

$$\left\{\frac{\text{CPI}-\text{adjusted Sales Price in the Last Yr}}{\text{CPI}-\text{adjusted Sales Price in the First Yr}}\right\}^{\frac{1}{\text{Yr diff b/w the last and the first sales}}} \tag{3}$$

The third alternative is created similarly. The main difference is that, rather than using the housing component of the area CPI-U, we deflate by the average value of all sales within each municipality during the specified year. Our thinking here was that each municipality acts as a separate segment within the larger northern New Jersey housing market. This consideration should automatically control for other attributes of municipalities that affect property sales prices, particularly those that are fiscally related. The formula for this municipal-oriented dependent variable is

$$\left\{\frac{\left(\text{Sales Price in the Last Yr}/\text{Sales Price in the First Yr})\right)}{\left(\text{Avg.Local Sales Price in the Last Yr}/\text{Avg.Local Sales Price in the First Yr}\right)}\right\}^{\frac{1}{\text{Yr diff b/w the last and the first sales}}} \tag{4}$$

[3] Following the example of the present piece, Chatman, Tulach and Kim (2012) apply this same method although with only repeat sales properties transacted before and after LRT (the RiverLine in southern New Jersey) began its service.

Table 2 - Summary of Descriptive statistics

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
Regressand						
AppRate	Appreciation rate: CPI adjusted	13,599	1.73	0.96	0.08	23.38
A_AppRate_CPI	Annual average appreciation rate: CPI adjusted	13,599	1.17	0.43	0.20	23.38
A_AppRate_Mket	Annual average appreciation rate: market adjusted	13,599	1.10	0.42	0.20	27.39
regressor						
NetD2HBLAsta	Network distance to the nearest HBLR Station (feet)	13,599	4,542.59	2,382.26	17.46	13,390.04
NetD2PATHsta	Network distance to the nearest PATH Station (feet)	13,599	15,702.81	8,585.22	2,641.53	38,523.67
D2CBD	Aerial distance to Jersey City CBD (feet)	13,599	19,375.18	7,687.19	1,844.56	38,916.81
D2HBLRtrack	Aerial distance to the nearest HBLR track (feet)	13,599	3,089.81	2,222.23	2.53	11,665.51
NetD2Hwyexit	Network distance to highway ramp (feet)	13,599	5,831.76	3,402.14	115.84	18,194.93
BLineAve	Properties near Bergenline Avenue Station	13,599	0.20	0.40	0	1
WSideAve	Properties near Westside Avenue Station	13,599	0.08	0.27	0	1
E22ndSt	Properties near East 22nd Street Station	13,599	0.06	0.24	0	1
9thSt	Properties near 9st Street Station	13,599	0.22	0.41	0	1
SATscore	Municipal average SAT score	13,599	1,264	58	1,192	1,406
MedHHInc1999	Median household income in 1999 ($) by Census Tract	13,599	38,977	10,188	12,376	83,441
P_WorkAGroup	% of working age group (18-54 yrs old) by Census Tract	13,599	0.56	0.05	0.47	0.88
P_FBornPop	% of foreign-born pop by Census Tract	13,599	0.40	0.17	0.02	0.74
1stSPrice_CPI	Sales price at the first transaction ($); CPI adjusted	13,599	221,613	125,212	30,248	1,282,156
1tSPrice_Mket	Sales price at the first transaction ($); market adjusted	13,599	177,440	194,101	2,757	4,998,686
Ratio_SPvsTAV	Ratio of sales price vs. tax assessment value	13,599	1.30	0.62	0.5	3.5
DiffYR	Year difference between the first and the last transaction	13,599	5.27	3.78	0	18
SalesFreqpost2000	Sales frequencies after 2000	13,599	1.67	0.93	0	6
PrePost1996	Properties sold pre-post year of Construction started	13,599	0.32	0.47	0	1
PrePost1994	2 Yr lag of Construction started; Anticipation Impact Dummy	13,599	0.19	0.39	0	1
PrePostSTAopOpen	Properties sold pre-post station opening	13,599	0.45	0.50	0	1
Union	dummy for Union City	13,599	0.05	0.21	0	1
Jcity	dummy for Jersey City	13,599	0.42	0.49	0	1
Bayonne	dummy for Bayonne	13,599	0.11	0.31	0	1

As table 2 describes, we included a range of regressors: proximity measures to different entities, neighborhood characteristics, and transaction features. We tested distinct effects for the three stations. These stations were chosen based on their distance to the JCCBD waterfront and the relative magnitude of hypothesized accessibility gains by HBLR. Both 22nd Street (8th street opened in 2011; out of our study period) in Bayonne and Westside Street in Jersey City are the furthest ends in south and southwest respectively. Only rare and inconvenient bus (or combined modes with PATH) access to NYC were available from the stations before the HBLR was even planned. Bergenline Avenue is not the furthest station in the north but as a densely mixed residential and commercial area the accessibility benefits within walking distance of the station would be larger than Tonnelle Avenue, the furthest. In fact, Tonnelle Avenues is mostly surrounded by industrial properties and few residential buildings (see figure 1; there were only few white dots, representing location of repeat sales' properties). Meanwhile, we included 9th Street Station in Hoboken for comparison purposes. It is not as far from CBD as the other three, but a high number of daily boardings (see table 1) would seem to reflect higher accessibility benefits from proximity to this station, which should result in improved home prices. Thus, we intend to examine net accessibility gains that highlight cost savings reflected in ridership propensity.

We used both network and aerial distances, albeit for different purposes. The former is applied for actual walking distances to the nearest HBLR station while the latter is used for more perceptional distances such as those to the CBD and to the HBLR track. As discussed earlier, since we focus upon accessibility to each station, actual network distance is preferred to some pre-defined buffer boundary. We recognize that a pre-defined boundary approach may be appropriate for estimating possible nuisance effects, which arise as a dampening of property prices very near stations and track. Nonetheless, we applied the network-distance gradient approach not only because it ameliorates possible bias in measuring the magnitude of transit capitalization, but also because we anticipate few negative externalities in the study areas. This is because much of the HBLR line, in fact, was aligned along the path of abandoned industrial rail track. Newly constructed sections, mostly along the JCCBD waterfront segments, are excluded from this study since they are within a half mile (800m) of PATH stations, which are more heavily used for commuting. More importantly, given relatively low accessibility gains expected from LRT compared to other rail systems in general, very short distance thresholds are not very meaningful since an insufficient number of homes in our sample of repeat sales lie within close proximity to the track.

We used selected socio-demographic information from the 2000 U.S. Census. Census tracts have long been used as proxies for neighborhoods (Goodman, 1985). The 2005-2009 5-year estimate from the American Community Survey (ACS) were not used due to a paucity of observations. In any case, 2000 Census data undoubtedly better represent the neighborhood characteristics for the broader period of sales records that we examine--1991 to 2009. Share of population that is in prime working age groups (between 18 and 54 years old), share of foreign-born population, and the median household income are included. We expected that a preponderance of working-age individuals causes home values to rise because this group is likely to put greater value on accessibility. We hypothesized that neighborhoods with high foreign-born populations enjoy the increased accessibility more than do other groups due to their high preference for public transit (urban areas outside of the U.S. tend to depend more on public transit), which should put upward pressure on home prices. Median household income, a proxy of neighborhood's economic status, was also expected to cause home price appreciation since being near higher-income groups should yield home price premia. In addition to tract-level data, the municipal-level average SAT test score was included, since school quality is an important consideration for in-migrants. We used the two-year average (2005-2006 and 2006-2007) SAT score for public school districts, which largely align with municipality boundaries.

Our model controls for the sales price of the first transaction since lower-priced homes tend to appreciate more rapidly. We also tested other related attributes – ratio of actual sales price vs. tax assessed value, the time that transpires between the first and the second (the most recent) sales, and a frequency of sales after operation of the HBLR – to see the relation with home price appreciation. Lastly, the year of HBLR ground breaking and a two-year lag of it were included to find effects of actual transit construction and partial effects of its anticipation, respectively.

To implement this study, two different property sales data sets of seven municipalities were used; one from online New Jersey state records (from 2000 to 2009) and the other from a private vendor, Econsult Corporation, which gained special access to earlier version of the state data set (from 1991 to 2002). After eliminating duplicate records, 149,037 single recorded transactions were trimmed to create appropriate repeat sales dataset. We first removed records with unrealistic sales prices – in particular sales records with prices below $1,000 and those with sales prices that were either more than 3.5 times or less than 50% than their assessed values since they suggest intrafamily transactions, possible input-coding errors, and the like. Further, records with prices in the highest and lowest percentile were dropped to minimize possible leverage issues from the observations. Consequently, 79,877 single sales records were left that enabled 17,435 repeat sales property observations in the dataset.

A range of geocoding efforts were invoked to add network and spatial attributes via ArcGIS software. First, we executed a GIS parcel match with parcel identifiers for each property; then for those unmatched addresses geocoding by each municipality was further implemented to prevent possible mis-geocoding across municipalities due to similar street identifiers. The result was that 14,068 geocoded repeat-sales properties between 1991 and 2009 remained. We then eliminated all repeat sales within a half mile of PATH stations for the final analysis. This effectively discarded properties in both the newly developed JCCBD waterfront and Jersey

City's CBD near Journal Square, and prevented any confounding impact from existing PATH accessibility on property value. In the end, we undertook our investigation with a data base that included 13,599 usable repeat-sales properties for seven municipalities that HBLR covers.

Model and Functional Form

Using the usual hedonic form (Cropper et al, 1988), we assume that the housing price equation takes the form

$$
\begin{aligned}
\mathrm{P}_i = {} & \beta_0 + \beta_1 \cdot \log(\mathrm{NetD2HBLAsta}) + \beta_2 \cdot \log(\mathrm{D2CBD}) + \beta_3 \cdot \log(\mathrm{D2HBLRtrack}) \\
& + \beta_4 \cdot \log(\mathrm{NetD2Hwyexit}) + \beta_{5,6,7,8} \cdot (\mathrm{BLineAve, WSideAve, E22ndSt, 9thSt}) \\
& + \beta_{9,10,11,12} \cdot \log(\mathrm{NetD2HBLAsta\ of\ BLineAve, WSideAve, E22ndSt, 9thSt}) \\
& + \beta_{13} \cdot \log(\mathrm{Median\ HH\ Income1999}) + \beta_{14} \cdot \%\ \mathrm{of\ Work\ Age\ Group} + \beta_{15} \cdot \%\ \mathrm{of\ FBornPop} \\
& + \beta_{16} \cdot \mathrm{SAT\ Score} + \beta_{17} \cdot \mathrm{Sales\ Price\ of\ the\ 1st\ transaction} \\
& + \beta_{18} \cdot \mathrm{Ratio\ of\ Sales\ Price\ vs.\ Tax\ Assesed\ Value} + \beta_{19} \cdot \mathrm{Year\ Difference\ bewteen\ sales} \\
& + \beta_{20} \cdot \mathrm{Sales\ frequency\ after\ 2000} \\
& + \beta_{21,22,23} \cdot (\mathrm{PrePost\ sales, PrePost2004, PrePost2006}) + \beta_{24,25,26} \\
& \cdot (\mathrm{Union, Jersey\ City, Bayonne}) + \epsilon
\end{aligned}
$$

$$\mathrm{P}_i = \beta_0 + \beta_1 D_i + \beta_2 N_i + \beta_4 S_i + \varepsilon \qquad (4)$$

Where **P** = log of property price appreciation

D_i= distance attributes

N_i= neighborhood attributes

S_i= stages of transaction attributes

β_j= parameters to be estimated

ε = error term

We start off using ordinary least squares (OLS) regression. We then apply robust regression, an automated algorithm (in Stata statistical software) that removes observations with extraordinarily large standardized residuals. It specially tends to target observations for which the dependent variable's value is close to its maximum and minimum – so called "leverage observations." By comparing the results from both OLS and robust regression we hope to learn the extent of heteroskedasticity induced by outlier and leverage observations, which removed in the course of applying robust regression.

Interpretation of Results

Table 3 presents our findings for six different specifications. We naturally found that robust regression yields higher R^2 than OLS, although both provide expected signs for the independent variables. Model 3 and Model 4 are the base models but between them apply two different price indices when obtaining the dependent variable, which is the properties' annualized appreciation rate. They include observations that sold twice pre-HBLR and/or post-HBLR. Model 5 and Model 6 are shown for the sake of comparison to Model 3 and Model 4. They focus on pre-post HBLR sales, which can eventually detect the extent of the temporal effects of increased accessibility.

Model 3 explains 37.2% of the variance inherent to annual home appreciation. The R^2 for Model 5, which limits observations to those for which the first sale occurred before and the second sale after the HBLR was operating, explains 52.3% of home appreciation – the highest fit of the six models. The lower R^2s in Model 4 and Model 6 suggest that producing constant home prices using municipally segmented housing market prices is empirically inferior to using a metro-wide CPI market price. Meanwhile, Model 1 used a dependent variable with total periodic appreciation: that is, it was not annualized. Despite the high R^2 in Model 1, the lack of annualization leads this model to be the least preferred.

Table 3 - Model Estimates

	Model 1 - Robust	Model 2 - OLS 1	Model 3 - Robust	Model 4 - Robust	Model 5 - Robust	Model 6 - Robust
VARIABLES	Appreciation rate	Annual Appreciation rate_CPI Adjusted	Annual Appreciation rate_CPI Adjusted	Annual Appreciation rate_Market Adjusted	Annual Appreciation rate_CPI Adjusted - Only PrePost Open sales	Annual Appreciation rate_Market Adjusted - Only PrePost Open sales
ln_NetD2HBLsta	0.0483***	-0.00129	0.00749***	0.00216	0.00739***	0.00057
	(0.0158)	(0.0121)	(0.0027)	(0.0021)	(0.0028)	(0.0023)
ln_D2CBD	-0.0516**	-0.000169	0.000671	-0.000748	-0.0118***	-0.00405
	(0.0248)	(0.0190)	(0.0043)	(0.0034)	(0.0040)	(0.0033)
ln_D2HBLRtrack	0.00599	0.0108	0.00196	0.00242*	0.000331	0.00202
	(0.0098)	(0.0075)	(0.0017)	(0.0013)	(0.0017)	(0.0014)
ln_NetD2Hwyexit	-0.0177**	-0.00157	-0.00287**	-0.00164	-0.00387***	-0.00317***
	(0.0074)	(0.0057)	(0.0013)	(0.0010)	(0.0013)	(0.0011)
BLineAve	0.261	0.0547	0.0417	0.0107	-0.0749**	-0.0443
	(0.1730)	(0.1320)	(0.0298)	(0.0234)	(0.0344)	(0.0281)
WSideAve	0.650***	0.253	0.156***	0.118***	0.113***	0.0406
	(0.2150)	(0.1640)	(0.0370)	(0.0290)	(0.0357)	(0.0292)
E22ndSt	0.547*	0.2	0.182***	0.0793**	0.153***	0.0774**
	(0.2890)	(0.2210)	(0.0497)	(0.0391)	(0.0431)	(0.0353)
9thSt	0.132***	-0.0364	0.0176***	0.00859*	0.0247***	0.00872**
	(0.0328)	(0.0251)	(0.0057)	(0.0044)	(0.0053)	(0.0044)
BLineAve_ln_NetD2HBLRsta	-0.0253	-0.00569	-0.00293	-0.000481	0.00915**	0.00608*
	(0.0203)	(0.0155)	(0.0035)	(0.0027)	(0.0041)	(0.0033)
WSideAve_ln_NetD2HBLRsta	-0.0803***	-0.0328*	-0.0194***	-0.0155***	-0.0155***	-0.00627*
	(0.0260)	(0.0199)	(0.0045)	(0.0035)	(0.0043)	(0.0035)
E22ndSt_ln_NetD2HBLAsta	-0.0681*	-0.0264	-0.0223***	-0.00965**	-0.0165***	-0.00857**
	(0.0349)	(0.0267)	(0.0060)	(0.0047)	(0.0052)	(0.0043)
9thSt_ln_NetD2HBLAsta	-2.19e-05***	7.35E-06	-1.96e-06*	-9.49E-07	-2.83e-06***	-0.00000118
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MedHHInc1999	8.65E-07	8.22E-07	4.25e-07***	-5.33E-08	5.56e-07***	3.72E-08
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Union	-0.0585**	0.0564***	0.0143***	0.0332***	0.000969	0.0162***
	(0.0239)	(0.0182)	(0.0041)	(0.0032)	(0.0036)	(0.0029)
Jersey city	-0.0785***	0.0201	-0.00301	0.00569**	-0.0106***	-0.000342
	(0.0184)	(0.0141)	(0.0032)	(0.0025)	(0.0029)	(0.0024)
Bayonne	-0.0564**	-0.0263	-0.000417	0.00681*	-0.0118***	-0.00243
	(0.0259)	(0.0198)	(0.0045)	(0.0035)	(0.0042)	(0.0034)
SAT score	0.000248**	0.000298***	3.83e-05*	8.31e-05***	1.95E-05	7.00e-05***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
P_WorkAGroup	0.351**	-0.0555	0.0541*	0.103***	-0.0209	0.0643***
	(0.1710)	(0.1300)	(0.0294)	(0.0230)	(0.0281)	(0.0228)
P_FBornPop	-0.0457	-0.0391	0.000808	0.00151	0.0235***	0.0187***
	(0.0467)	(0.0357)	(0.0080)	(0.0063)	(0.0079)	(0.0064)
Ratio_SPvsTAV	-0.391***	-0.0992***	-0.0657***	-0.0430***	-0.0724***	-0.0434***
	(0.0093)	(0.0071)	(0.0016)	(0.0012)	(0.0017)	(0.0014)
DiffYR	0.0419***	-0.0386***	-0.0101***	-0.00646***	-0.0131***	-0.00544***
	(0.0019)	(0.0014)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
SalesFreA2000	0.104***	0.0388***	0.0159***	0.00849***	0.00414***	0.00464***
	(0.0055)	(0.0042)	(0.0009)	(0.0007)	(0.0009)	(0.0007)
PrePostSTAOPEN	0.0774***	0.0203**	0.0129***	-0.00458***		
	(0.0111)	(0.0085)	(0.0019)	(0.0015)		
PrePost1994	-0.285***	0.0498***	-0.00784***	0.0138***	0.0155***	0.0172***
	(0.0153)	(0.0117)	(0.0026)	(0.0021)	(0.0027)	(0.0022)
PrePost1996	-0.148***	-0.0284**	-0.0331***	-0.0124***	-0.0122***	-0.00628***
	(0.0148)	(0.0113)	(0.0025)	(0.0020)	(0.0025)	(0.0021)
1stSPrice_CPI	-0.361***	-0.213***	-0.0545***		-0.0431***	
	(0.0101)	(0.0077)	(0.0017)		(0.0018)	
1tSPrice_Mket				-1.14e-07***		-1.01e-07***
				(0.0000)		(0.0000)
Constant	5.915***	3.600***	1.725***	0.942***	1.842***	1.025***
	(0.3300)	(0.2520)	(0.0568)	(0.0431)	(0.0541)	(0.0428)
Observations	13,599	13,599	13,599	13,599	6,151	6,151
R-squared	0.416	0.192	0.372	0.272	0.523	0.359
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1						

Our models show that properties closest to HBLR stations display lower-than-average home appreciation rate in general. Proximity to highways, on the other hand, continues to play a positive role in home price appreciation despite their long-established nature. Recall, however, that locations and distances for the HBLR's distant stations were our main research focus. Based on interpretation of the coefficients of dummy variables in semi-logarithmic regressions (Halvorsen and Palmquist, 1980), properties near the West Side Ave station experienced annual price appreciation of nearly 16.9 (12.0 in Model 5) percentage points greater than for other properties in the study area. The premium was 20.0 (16.5 in Model 5) percentage points for properties near the East 22nd Street station. The coefficient of the binary variables denoting 9th Street was also statistically significant although the relative small size of the coefficient implies a weaker rate of price appreciation. There is no significant magnitude and sign for properties near Bergenline Ave station. As described earlier, Bergenline Avenue is located in Union City where the bus network to Manhattan was already superior to that at the other stations. The fact that good public transportation to a major job hub already existed there implies few new significant accessibility gains at Bergenline Avenue. This set of results supports our hypothesis that the newly created accessibility by HBLR was capitalized at stations farthest from the CBD. Also, although ridership count is associated with accessibility benefits, these results support the notion that distance of a station from the CBD has greater influence on households' cost savings. Of course, individual property appreciation truly is a household-based measure, while ridership change is more collective in nature, and indicative of how many households are affected.. Thus, the overall net benefit to an area of a particular transit facility is some combination of both.

Looking into station-specific effects, as one moves away from the West Side Ave and East 22nd Street stations, properties appreciate by about one percentage point (the coefficients are 0.96

and 1.1, respectively) for every 50 feet (or 15 meters--a typical lot width in an urban area). This implies that the station-based premium fully dissipates within a quarter mile (400 meters) of the stations. Thus a quarter-mile buffer appears to exist for the HBLR, whereas a half mile (800 m) appears appropriate for PATH, perhaps due to its greater age and direct connections to Manhattan. This all supports the Alonso-Wingo-based hypothesis that properties around the HBLR stations most-distant from the CBD should capitalize more value from a new transit offering due to the larger transportation cost savings potentially generated there.

Properties in municipalities with higher-than-average student SAT scores tended to appreciate more rapidly than did properties in municipalities where average SAT scores were lower. But, the small coefficient suggests a marginal impact on the price appreciation. The share of working-age group is positively associated with home appreciation rate. The shares of foreign-born population revealed no significant effect on home appreciation rates in our base model (Model 3 and Model 4). Yet, they were influential in Model 5 and Model 6. This implies higher temporal accessibility gains in the areas of high foreign-born population than others. This supports the hypothesis that improved accessibility should demonstrate a greater capacity to capitalize in communities that exhibit attributes suggesting greater transit dependence.

Table 3 displays interesting period attributes as well. Overall, they show higher annualized home appreciation for homes that were held for longer periods prior to their sale. Despite controlling for the inflation in the housing component of the price index, this effect from ownership duration may reflect some sort of anomalous nonlinearity in home appreciation in the immediate area during the housing market boom through 2007.. According to Model 3, no statistically detectable capitalization in housing took place during construction and planning stages of the HBLR (i.e., the housing market adjusted to the transit investment just before it was put in place). The coefficient of pre-post HBLR sales, however, point strongly to the positive impact of an operating HBLR on home prices. On the other hand, once we limit the sample to those homes that had a first sale prior to the start of HBLR operations and that had the second sale after it began operating,(Model 5), we did find some evidence of capitalization during the HBLR's planning stages. The difference between the models appears to be due to the inclusion of both pre-HBLR (even pre-construction) and post-HBLR only samples in Model 3, which may have led to bias in (distortions to) the coefficients due to omitted variables such as those factors that led to the housing market bubble, rather than improved accessibility via the HBLR. Finally, property prices in the study area display the usual equilibrating effect; that is, lower-valued properties tended to appreciate more rapidly than did higher priced ones. In fact, it shows that those properties nearest HBLR stations, in least developed areas farthest from the CBD, tended to appreciate most as predicted by Alonso-Wingo theory.

Across the six models in Table 3 models, the signs and statistical significance of key explanatory variables relating to accessibility are generally the same. This robustness across specifications lends added credence to the overall analysis. Still, dissimilar parameter magnitudes do exist across models. They tend to be somewhat more-intense when robust regression is applied to the CPI-adjusted appreciation rate when compared to models for which the dependent variable is municipally price-adjusted.

Conclusions

In this study we demonstrated unequivocally that light rail can have a positive impact on property appreciation rates near urban commuting stations. We arrived at this finding by focusing our analysis on properties near stations in the urban periphery that would receive the most benefit from a new transit system as the Alonso-Wingo model predicts. At these stations, we found that properties appreciated at an annual average rate of 18.4 percentage points higher than did other study-area properties. The appreciation premium evaporates rather rapidly, at about one percentage points per every 50 feet. Hence, the appreciation premium appears to dissipate completely within a quarter mile of the stations. This is a somewhat shorter distance than reported in other studies. This leads us to question, even more strongly, the theoretical validity of the usual practice of applying arbitrarily developed buffer zones (binary variables) to valuate distance to stations, as opposed to the gradient approach that we apply.

Our study is striking among hedonic studies on transit's impact on property values. We collectively examined changes in the values of individual properties with multiple appreciation ratios, and tested how both a distance from the nearest station and its distance from the CBD are related to the price change. Almost all have, instead, valuated transit's impact on property values using cross-sections or, at best, pooled cross-sections (Voith, 1993). The problem with using standard cross-sections is that transit lines are often built where population densities and properties values are high (so as to assure ridership and a reasonable revenue stream) and to move people with cars off the road and onto transit. In sum, a transit system, by design, is likely to be placed in high-priced neighborhoods. Hence, nowadays it is then not clear when evaluating on property values whether the rail's placement caused property prices to rise or whether high property prices near a transit system are what enticed the light rail to locate where it is. There is no reason not to expect that the latter is why researchers have been finding high property values near transit lines. We are aware of few studies on the property-value impacts transportation systems have examined repeat sales data. Yet, their approaches were also limited to either compare gradients based on pooled cross-sessions of data in different time periods (McMillen and McDonald, 2004) or to test pre-post LRT sales only with no annualized appreciation adjustment (Dan, Tulach, and Kim, 2012).

Because we were concerned about the effects of different housing market cycles across an area even as small as Hudson County, we decided to normalize property sales prices by municipality to identify relative annualized appreciation rates of properties. It appeared not to be superior to prices normalized by the housing component of the metropolitanwide consumer price index. Still, this innovation may prove useful in other future research.

Despite our contributions to the literature, we note a couple of avenues that need further investigation. More works need to be undertaken to give analysts a better understanding of the ideal period of study for property value change near transit facilities. While we based our examination on available literature by Agostini (2008) and McDonald & Osuji (1995), we study properties using a somewhat arbitrarily selected two-year prior with respect to station openings in order to capture any "anticipation effect" of new investments in the end. We seem to have derived some evidence for anticipatory effects. The duration of post-operation appreciation on the other hand, has not yet been studied inasmuch as our review of the extant literature has revealed. Similarly, we did not uncover much evidence, despite an attempt. Perhaps, our "nonfindings" derived from a lack of sales records for those properties near the stations of prime interest, which opened as recently as 2006. Hence, additional exploratory analysis of this issue should be quite useful to others using repeat sales data.

Another issue with our data set was that too few of the observations were accompanied by characteristics of the properties (structure's living space, structure's age, lot size, floor-to-area-ratio, stories, number of bedrooms, number of bathrooms, number of kitchens, presence of a garage, architectural differences, etc.). While Coulson and Lahr (2005) suggested that changes in these property attributes may not be important, they also show that such characteristics do, in fact, help determine appreciation rates, at least for assessed property values. Hence, it would be worthwhile to pursue this line of inquiry to confirm or reject Wang and Zorn's (1997) conjecture that one need not specify critical characteristics when using the repeat sales approach.

Reference

1. Agostini, C., Palmucci, G. (2008) The anticipated capitalisation effect of a new metro line on housing prices *Fiscal Studies* 29 233–256.

2. Alonso, W. (1964) *Location and Land Use: Toward a General Theory of Land Rent*. (Harvard University Press., Cambridge., MA)

3. Armstrong, R. (1994) Impacts of commuter rail service as reflected in single-family residential properties *Transportation Research Record* 1466 444-472.

4. Bailey, M., Muth, R., Nourse, H. (1963) A regression method for real estate price index construction *Journal of the American Statistical Association* 58 933-942.

5. Bajic, V. (1983) The effects of a new subway line on housing prices in metropolitan Toronto *Urban Studies* 20 147-158.

6. Bartholomew, K., Ewing, R. (2011) Hedonic Price Effects of Pedestrian- and Transit-Oriented Development *Journal of Planning Literature* 26 18-34.

7. Bowes, D., Ihlanfeldt, K. (2001) Identifying the impacts of rail stations on residential property values *Journal of Urban Economics* 50 1-25.

8. Boyce, D., Allen, B., Mudge, R., Slater, P., Isserman, A. (1972) *Impact of Rapid Transit on Suburban Residential Property Values and Land Development* the U.S. Department of Transportation. (University of Pennsylvania) NTIS No. PB220693

9. Breuckner, Jan K. (1982) A note on sufficient conditions for negative exponential population densities. *Journal of Regional Science* 22 353-359.

10. Cervero, R., Duncan, M. (2002) Transit's value-added: Effects of light and commuter rail services on commercial land values *Transportation Research Record* 1805 8-15.

11. Chatman, D., Tulach, N., 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* 49 467-487.

12. Chen, H., Rufolo, A., Dueker, K. (1998) Measuring the impact of light rail systems on single-family home values: A hedonic approach with geographic information system application *Transportation Research Record* 1617 38-43.

13. Coulson, E., Lahr, M. (2005) Gracing the land of Elvis and Beale Street: Historic designation and property values in Memphis *Real Estate Economics* 33 487-507.

14. Cropper, Maureen L., Deck, Leland B., McConnell, Kenneth E. (1988) On the choice of functional forms for hedonic price functions *Review of Economics and Statistics* 70 668-675.

15. Damm, D., Lerman, S., Lerner, E., Young, J. (1980) Response of urban real estate values in anticipation of the Washington Metro *Journal of Transport Economics and Policy* 14 315-336.

16. Debrezion, G., Pels, E. 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) 161-180.

17. Dewees, D. (1976) The effect of a subway on residential property values in Toronto *Journal of Urban Economics* 3 357-369.

18. Dornbush, D. (1975) BART-induced changes in property values and rents, in Land Use and Urban Development Projects: Phase I, BART Impact Study U.S. Department of Housing and Urban Development, and U.S. Department of Transportation.

19. Dowall, D. (1980) Methods for assessing land price effects of local public policies and actions, In J. Thomas Black and James Hoben (eds) Urban Land Markets, Price Indices, Supply Measures, and Public Policy Effects *ULI Research Report* 30 161-183.

20. Fernald, J G. (1999) Roads to prosperity? Assessing the link between public capital and productivity *American Economic Review* 89 619-638.

21. Garrett, T. (2004) Light-Rail Transit in America - Policy Issues and Prospects for Economic Development Federal Reserve Bank of St. Louis.

22. Giuilano, G. (1989) New directions for understanding transportation and land use *Environment and Planning A* 21 145-159.

23. Glaeser, E., Kohlhase, J. (2004) Cities, regions, and the decline of transportation costs *Papers in Regional Science* 83 197-228.

24. Goetz, E., Ko, K., Hagar, A., Hoang, T. (2009) Differential Impact of the Hiawatha Light Rail Line on Property Values in Minneapolis, Paper Presented at Transportation Research Board 88th Annual Meeting.

25. Goetzmann, W N., Spiegel, M. (1995) Non-temporal components of residential real estate appreciation *Review of Economics and Statistics* 77 199-206.

26. Goodman, A. (1985) A note on the size and measurement of segregation indices *Journal of Regional Science* 25 471-476.

27. Graybeal, R., Gifford, J. (1968) Impact model of transportation systems on land values *Annals of Regional Science* 2 153-160.

28. Halvorsen, R., Palmquist, R. (1980) The Interpretation of dummy variables in semilogarithmic equations *American Economic Review* 70 474-475.

29. Hess, D., Almeida, T. (2008) Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York *Urban Studies* 44 1041-1068.

30. Huang, H. (1996) The land-use impacts of urban rail transit systems *Journal of Planning Literature* 11 17-30.

31. Jackson, K. (1985) Crabgrass *Frontier: The Suburbanization of the United States*. New York: Oxford University Press.

32. Knight, R., Trygg, L. (1977) Evidence of land use impacts of rapid transit systems *Transportation* 6 231-47.

33. Langley, C J. (1981) Highways and property values: The Washington beltway revisited *Transportation Research Record* 812 16-21.

34. Lee, D. (1973) Case Studies and Impacts of BART on Prices of Single Family Residences Institute of Urban and Regional Development, University of California at Berkeley.

35. Li, M., Brown, J. (1980) Micro-neighborhood externalities and hedonic house prices *Land Economics* 56 125-141.

36. Manson, D M. (1981) The negative exponential density gradient and the standard radius: mathematical and empirical relationships *Environment and Planning A* 13(9) 1059-1065.

37. McDonald, J., Osuji, C. (1995) The effect of anticipated transportation improvement on residential land values *Regional Science and Urban Economics* 25 261-278.

38. McMillen, D P., McDonald, J. (2004) Reaction of house prices to a new rapid transit line: Chicago's Midway Line., 1983 -1999 *Real Estate Economics* 32(3) 463-486.

39. Ryan, S. (1999) Property values and transportation facilities: Finding the transportation-land use connection *Journal of Planning Literature* 13 412-427.

40. Voith, R. (1993) Changing capitalization of CBD-oriented transportation systems: Evidence from Philadelphia, 1970 – 1988 *Journal of Urban Economics* 33 361-376.

41. Wang, F., Zorn, P. (1997) Estimating house price growth with repeat sales data: What's the aim of the game? *Journal of Housing Economics* 6 93-118.

42. Weinstein, B., Clower, T., Gross, H. (1999) The Initial Economic Impacts of the DART LRT System Center for Economic Development and Research, University of North Texas.

43. Xie, F., Levinson, D. (2010) How streetcars shaped suburbanization: a Granger causality analysis of land use and transit in the Twin Cities *Journal of Economic Geography* 10 453 – 470.