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Rail transit investment and property values: An old tale retold

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ABSTRACT

Although a number of researchers have used the hedonic pricing model to value transit improvements by comparing prices of real estate properties within a certain distance from a transit station with those beyond that distance, the accuracy of these assessments is subject to questioning due to methodological limitations. By analyzing single-family and multi-family property sale transactions in Los Angeles (CA) during 2003 and 2004, this spatial hedonic study examines how the property value effects of rail transit can become volatile depending on housing markets, rail transit technologies, near-station land uses and transit development phases. By contrasting results from the spatial Durbin models and the Geographically Weighted Regression models with those from the conventional Ordinary Least Squares approach, the study shows the estimation accuracy can be improved considerably by controlling for the spatial dependence effect. Proximity to mature rail transit stations generally benefits multi-family property values, but the effect is negative for single-family properties. Residents (especially those from single-family households) seem to favor proximity to heavy rail transit more than light rail services. The premiums for rail transit accessibility also largely depend on different development phases and can be heavily discounted by the existence of Park-and-Ride facilities. This study provides policy makers with new empirical evidence and analytical tools to revisit value capture as a financing alternative and to reform investment strategies for rail transit services.

1. Introduction

Transit systems bring societal benefits such as congestion relief, social equity improvement, emissions reduction and economic development (Boarnet et al., 2013; Mohammad et al., 2013). Thus, improving and expanding rail transit systems has been on the agenda in many cities (Peter et al., 2013). In order to justify their investment, policy makers often argue that rail transit systems can potentially benefit property values, and as a result, may choose value capture as one of the financing means. However, the literature is still unsettled regarding the effect of rail transit systems on property values. Numerous previous studies have found that transit accessibility benefited property values (Al-Mosaind et al., 1993; John, 1996; Landis et al., 1995), but others have reported negative effects (Chen et al., 1998; Weinstein and Clower, 1999). The mixed findings might be partly due to different socio-demographic and land use contexts, as well as model estimation biases (Debrezion et al., 2007; Kuminoff et al., 2010; Mohammad et al., 2013). Because previous hedonic studies on transit accessibility mainly relied on Ordinary Least Squares (OLS) regression, the estimates were likely biased due to the lack of control for the spatial dependence effect, which reveals a complex and intertwined relationship among housing transactions. For example, Kuethe (2012) found that land use diversity had a positive impact on housing prices using an OLS model, while such an impact became statistically non-significant after controlling the spatial dependence effect.

This study, by controlling for such an effect, examines how rail transit accessibility impacts both multi-family and single-family property values in Los Angeles during 2003–2004. Our study sheds light on this long lasting but unsettled policy debate by making the following contributions. First, based on our unique study site and period, we reveal that premiums for rail transit accessibility can be volatile depending development stages, housing markets, and near-station land uses (particularly the availability of Park-and-Ride facilities). While some previous studies discussed the volatility in a piecemeal fashion and in different cities, we examine it comprehensively in the same city. Second, we introduce a novel spatial modeling system and compare it with the conventional OLS approach; we improve estimation accuracy by controlling for the spatial dependence effect. The remainder of this paper is organized as follows. In the next section, we present a literature review relevant to the hedonic analysis of rail transit. Then we introduce study design, model specifications, and results. Finally, we provide concluding remarks and discuss policy implications.

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2. Literature review

In Table 1, we summarize the analytical methods and results of recent hedonic studies on the property value impact of rail transit access. Consistent with meta-analyses by Debrezion et al. (2007) and Mohammad et al. (2013), we found that rail transit systems influence property values in both positive and negative directions and at various magnitudes. These findings may be attributed to different methods, various contexts, different rail systems and property types.

Most previous studies found positive property value impacts of rail transit systems and many of them relied on the OLS method (Billings, 2011; Bowes and Ihlanfeldt, 2001; Cervero and Duncan, 2002b; Duncan, 2008; Hess and Almeida, 2007; Pan, 2013; Pan et al., 2014; Yan et al., 2012). A handful of studies conducted in Asian cities, such as Bangkok, Thailand (Chalermpong, 2007), Seoul, Korea (Cervero and Kang, 2011), Beijing, China(Zhang et al., 2014) and Shanghai, China (Pan et al., 2014), found positive impacts on property values. Researchers have also reported positive impacts in European cities/countries, such as Netherlands (Debrezion et al., 2006), Helsinki, Finland (Laakso, 1992), and London, UK (Gibbons and Machin, 2003). Compared to American cities, the impacts were generally higher in European and Asian cities, where access to private transportation is more limited and transit-oriented cultures are stronger (Debrezion et al., 2007; Mohammad et al., 2013; Mulley, 2014).

However, rail system effects on property values may vary, depending on types of technology, development stages, housing markets and land-use characteristics around the station areas. For example, rail transit systems can be either light rail transit (LRT) or heavy rail transit (HRT); these two types of systems differ in terms of construction cost and carrying capacity, but their land use implication has not been well discussed (Zhang et al., 2014). Even though Cervero and Landis (1997) found no large scale land value changes associated with the transit system in San Francisco after 20 years of operation, most previous studies confirmed that transit might have some positive property value impact. Agostini and Palmucci (2008) identified anticipated capitalization of the transit system in Santiago, Chile; Yan et al. (2012) found that the property value impact of rail transit systems was negative before the opening of the system, but shifted to positive in the operational phase. In contrast, Ko and Cao (2013) indicated that houses in the vicinity of transit stations may already have higher prices before the introduction of a transit system and argued that the premium for the proximity to rail stations may be attributed to other location factors. Mathur and Ferrell (2013) found no anticipated capitalization before the rail system's opening, and they further found that positive property value impacts existed only during Transit Oriented Development (TOD) construction and after the construction.

Single-family housing prices, especially in middle-income neighborhoods, often react negatively or neutrally to rail transit accessibility (Cervero and Duncan, 2002a). However, access to rail systems can be capitalized at a higher extent for multi-family properties than for single-family properties (Cervero and Duncan, 2002a; Duncan, 2008). Multi-family residences generally better align with TOD criteria than do single-family houses.

Moreover, the effects may depend on context-specific land use characteristics. Capitalization effects are usually associated with walkable residential neighborhoods (Duncan, 2010a), healthy economies (Cervero, 2006), proactive and encouraging land use planning (Cao and Porter-Nelson, 2016; Mejia-Dorantes and Lucas, 2014), and land use intensification and development along the transit systems (Cervero and Kang, 2011), particularly for residential uses. Du and Mulley (2007) found large variations (ranging from −42% to 50%) depending on location in England. Carlton et al. (2012) and Bowes and Ihlanfeldt (2001) also found large variations in their San Diego and Atlanta case studies, respectively. Concerning developing countries, researchers have found higher magnitudes and greater catchment areas of public transit systems (Jun, 2012; Xu and Zhang, 2016).

However, there is no widely accepted agreement about how the above factors influenced residents' preferences toward the rail systems. Moreover, most previous studies employed the Ordinary Least Squares regression technique and their estimates may be potentially biased and inconsistent due to the lack of control for the spatial dependence effect (Ibeas et al., 2012). According to Anselin (1988), such an effect describes the relationship between the price of a house and the price and various characteristics of nearby properties. Previous researchers, such as Li and Saphores (2012b) and Redfearn (2009), have shed light on this issue in their empirical analyses. In a complex urban housing market, such a spatial relationship violates a basic assumption of linear regression–that observations are independent from one another (LeSage and Pace, 2009). Numerous spatial regression techniques (LeSage and Pace, 2009) have been developed to address this issue (LeSage, 1999).

3. Methodology

3.1. Research questions

This study contributes to literature and the policy debate about whether proximity to rail transit benefits property values, by exploring the following questions. First, is there a need to control for the spatial dependence effect to obtain unbiased estimates? Second, does the property value impact of rail transit differ by housing market type, development stage, rail technology and near-station land use characteristics? To answer the first question, we estimate spatial regression models and compare the results with those from OLS models. To answer the second question, we estimate the models for multi-family and single-family markets separately and add several relevant interaction terms into the models.

3.2. Study area and period

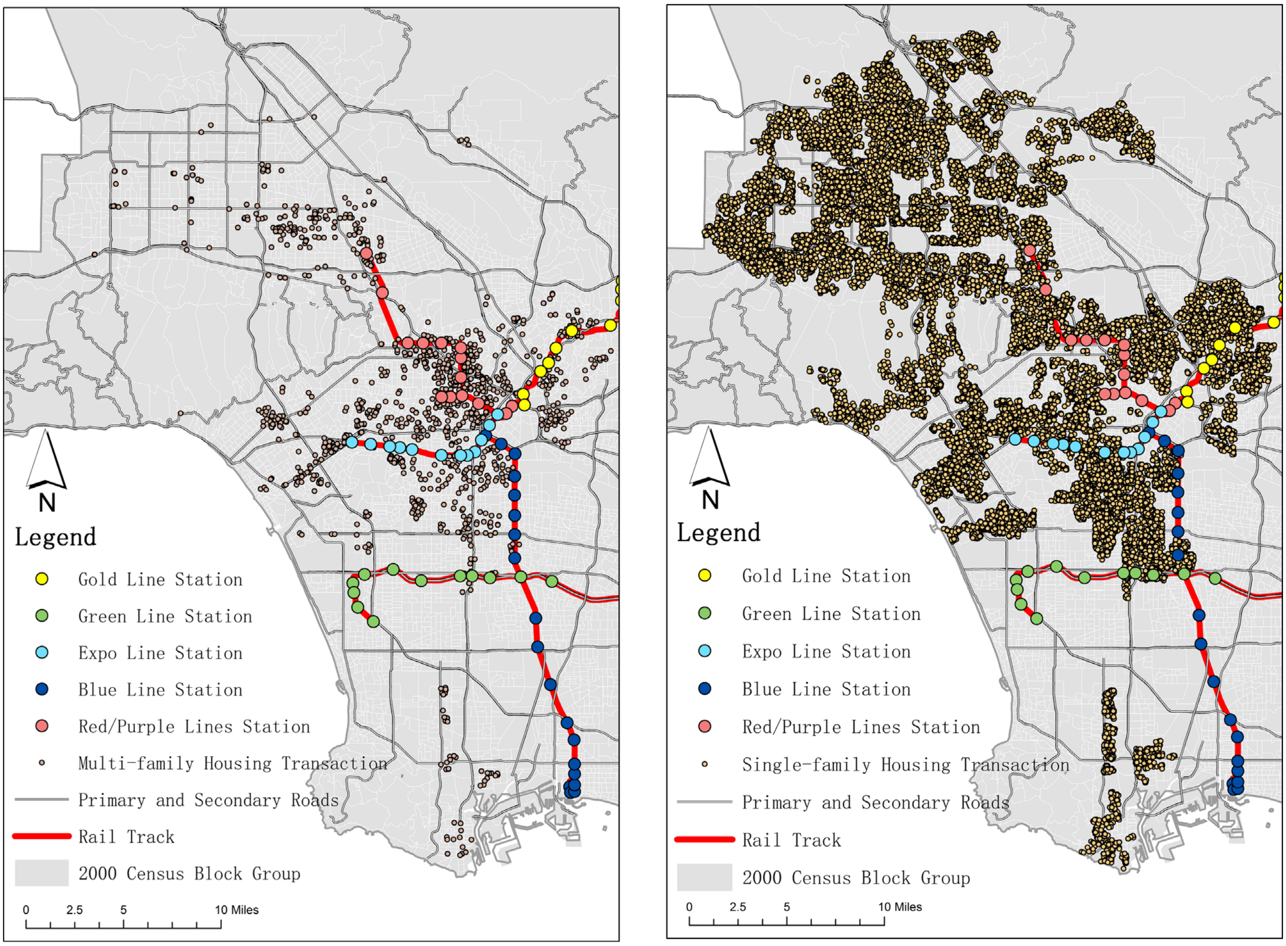
We analyze single-family and multi-family property sale transactions in Los Angeles during 2003–2004 (see Fig. 1). Los Angeles is regarded by many researchers as an example of urban sprawl and auto-dependent development (Ewing, 1997; Wachs, 1996). During the 1980s, the Los Angeles County Metropolitan Transportation Authority began to build consensus among multiple stakeholders about adding a rail transit system (named LA County Metro Rail, or LACMR in this paper) and raised funds from various sources (Wachs, 1996). The first rail transit line opened in 1990; since then, vast investments have expanded and enhanced the system.

In 2003–2004, the LACMR consisted of 5 lines (Red, Purple, Blue, Green, and Gold) with 70 stations; such a study period affords a valuable opportunity to investigate different development phases in one city's transit system during the same time period. The Red Line, opened in different stages between 1993 and 2000, stretched from downtown Los Angeles to Hollywood; the Purple Line (Union Station to Wilshire/Western Station) opened in 1996. Together, the Red and Purple Lines were two heavy rail lines (mainly underground), and were also the busiest LACMR lines. The Blue Line (opened in 1990, from downtown Los Angeles to downtown Long Beach), Gold Line (opened in 2003, from downtown Los Angeles to Pasadena) and Green Line (opened in 1995, from Redondo Beach to Norwalk) were three light rail lines. By

Table 1.
Summary of previous hedonic studies about the property value impact of rail transit.

Author	Location	Transit type	Property type	Analytic method	Key results
Gatzlaff and Smith (1993)	Miami (FL), USA	M	R	Repeat Sales Indices and Ordinary Least Squares (OLS)	Weak impact varies by neighborhood type.
Landis et al. (1995)	California, USA	L, T	S, CM	OLS	$4.36 higher/meter closer to stations; effects on commercial property vary.
John (1996)	Washington, D.C., USA	M	A	OLS and Three-stage Least Squares	$2.5 increase by one-tenth mile closer.
Chen et al. (1998)	Portland (OR), USA	L	S	OLS	Both positive and negative effects; positive effects dominate.
Bowes et al. (2001)	Atlanta region (GA), USA	R	S	OLS	Capitalization effects vary with neighborhood income level, distance to downtown, and distance from the station.
Weinberger (2001)	Santa Clara County (CA), USA	L	CM	OLS	Higher lease rate within 0.5 mile from station.
Cervero and Duncan (2002b)	Santa Clara County (CA), USA	L, C	CM	OLS	Prices are 23% higher for a typical commercial parcel near a light rail transit stop. Premiums of 120% for commercial land are found in a business district and within 0.25 mi of a commuter rail station.
Cervero (2006)	San Diego (CA), USA	L, C	M, S, CN, CM	OLS	Positive effects found; relationships vary by corridor and land-use type.
Hess and Almeida (2007)	Buffalo (NY), USA	L	R	OLS	Proximity effects are positive in high-income station areas and negative in low-income station areas; effects are statistically more significant in network distance while greater in straightline distance.
Duncan (2008)	San Diego MSA (CA), USA	L, C	S, CN	OLS	Condominiums receive capitalization benefits beyond 10%; benefits received by single-family properties fall within 10%.
Ko and Cao (2013)	Minneapolis (MN), US	L	CM, I	OLS	Within 0.25 mile, Commercial building values increase 38% and demand for industrial buildings decreases.
Cervero and Kang (2011)	Seoul, Korea	B	R, CM	Multilevel Logit Model	10% land price premiums for residences within 300 m of stations and more than 25% for retails and non-residential within 150 m.
Billings (2011)	Charlotte (NC), USA	L	S, CN, CM	OLS & Repeat Sales Model	Sale prices for single-family properties within 1 mile of stations increase 4.0%, and 11.3% for condominiums; no neighborhood impacts found for commercial properties.
Yan et al. (2012)	Charlotte (NC), USA	L	S	Fixed Effect Model	Desire to live closer to a light rail station increases when transit system becomes operational.
Dubé et al. (2013)	Montreal, Canada	C	S	Difference-in-Difference	Premiums are found for houses located within walking distance to stations.
Pan et al. (2014)	Houston (TX), USA and Shanghai, China	L, S	R	Multilevel Regression Model	Impact is significantly positive in both study sites.
Zhang et al. (2014)	Beijing, China	B, L, M	R	OLS	Every 100 m closer, $ 39.41 premium for M, $17.57 premium for L.
Mulley (2014)	Liverpool, UK	R	B	Geographically Weighted Regression	Accessibility varies significantly over geographical space.

Notes: 1. Transit Type: L=Light Rail, T=Trolley, H=Heavy Rail, C=Commuter Rail, B=Bus Rapid Transit, S=Subway, M=Metro Rail Transit, R=Rapid Rail Transit, I=Industrial Property. 2. Property Type: A=Apartment, S=Single-family House, M=Multi-family House, CN=Condo, CM=Commercial Property, L=Land Value, R=Residential Property.



(a) Multi-family Sample (b) Single-family Sample

Fig. 1. Maps of rail transit systems and home sale locations during 2003–2004 in Los Angeles. (a) Multi-family Sample, (b) Single-family Sample. Notes: the maps show existing and proposed station locations as of 2003. The locations of EXPO line stations were determined according to the version announced to the public. Maps were made from data provided by Los Angeles County GIS Data Portal.

selecting this study period, we also avoided the housing market crash of later years; because it was a relatively short period with no severe market shocks, it helped to satisfy the market equilibrium assumption (Rosen, 1974) of hedonic analysis.

We chose 2003–2004 as the study period because during this period, different phases of the LACMR co-existed: Purple/Red Lines, Blue Line and Green Line were mature lines with 10, 13 and 8 years of operation respectively; the Gold Line had just opened, and the EXPO Line was at the planning stage when the draft routing and station locations had been announced to public. These different development phases allowed us to investigate the capitalization effects of rail transit amenities in different development stages. We delineate our study area within the city boundary of Los Angeles in order to control for the factors of housing market and municipal policies/services; there were a total of 57 stations within the city boundary.

3.3. *Data and variables*

Table 2 presents summary statistics for the multi-family and single-family samples. The housing transaction data were obtained from DataQuick Information Systems (now part of CoreLogic Inc.). The original dataset included 2909 multi-family transactions and 24,570 single-family transactions. Following the recommendations of Li and Saphores (2012a, 2012b), we excluded observations that had missing or extreme values on variables included in the model. In addition, we eliminated multi-family and single-family records with fewer than 3 neighboring sales within their neighborhood boundary developed by the research team of Zillow Inc. Researchers have believed that capitalization effects would be extremely small when the distance to a rail station exceeds one mile (Duncan, 2010a; Yan et al., 2012); other studies have modeled accessibility variables beyond one mile (Bowes and Ihlanfeldt, 2001; Pan, 2013). In their meta-analysis, Debrezion et al. (2007) posited that rail station impacts would be negligible beyond a distance of two miles from a station. In this study, we excluded observations beyond 3 miles from a station. Our final multi-family sample included 958 records and our final single-family sample included 10,078 records.

A quarter mile is the commonly used distance threshold within which Americans are willing to walk to a transit station (Nagel et al., 2008). We included three dummy variables to represent the proximity to transit stations: within 400 m (0.25 mile) of the nearest station, 400 m to 800 m (0.5 mile) from the nearest station, and 800 m to 1600 m (1 mile) from the nearest station. Kahn (2007) found that the availability of Park-and-Ride facilities was a prominent land use feature reflected in property values. We examined the Park-and-Ride facilities for each station by checking detailed station information at the Metro website with reference to Google Earth images and created a dummy variable for the availability of such facilities.

Following the theoretical framework of hedonic studies, we

Table 2.
Summary statistics.

Variable	Description	Multi-family houses (n=958)				Single-family houses (n=10,078)			
		Mean	**Standard deviation**	**Minimum**	**Maximum**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
Dependent variable									
PRICE	House sale price ($1000)	1035.07	1365.29	100.00	19,597.00	505.14	383.70	45.00	5300.00
House characteristics variables									
PAREA	Area of parcel (m^2)	857.72	703.48	267.07	16,995.45	648.11	400.91	61.97	10,152.24
SAREA	Area of structure (m^2)	678.31	547.18	153.85	7643.41	153.42	80.06	30.40	1126.00
UNIT	Number of units	9.42	7.26	5	120				
BATHRM	Number of bathrooms	11.04	9.52	3	120	1.77	0.97	1	30
BEDRM	Number of bedrooms	13.37	10.27	5	132	2.76	0.98	1	20
B_POOL	Binary: 1=house has a pool	0.05	0.21	0	1	0.09	0.28	0	1
AGE	Age of house in the sale year	54.32	23.09	0	119	67.64	21.28	0	124
Neighborhood characteristics variables									
B_PARK	Binary: 1=neighborhood park within 200 m	0.07	0.26	0	1	0.07	0.26	0	1
B_SPRMK	Binary: 1=supermarket within 200 m	0.13	0.34	0	1	0.03	0.18	0	1
B_MSM	Binary: 1= museum/cultural attraction within 200 m	0.02	0.13	0	1	0.00	0.06	0	1
B_HWY	Binary: 1=highway lane within 250 m	0.17	0.38	0	1	0.11	0.31	0	1
B_RAIL	Binary: 1=rail track within 250 m	0.07	0.26	0	1	0.08	0.28	0	1
B_PWRLN	Binary: 1=high-voltage power line within 250 m	0.11	0.31	0	1	0.13	0.34	0	1
B_LNDFL	Binary: 1= active landfill site within 2500 m	0.11	0.32	0	1	0.15	0.35	0	1
B_BUS	Binary: 1=bus stop within 500 m	0.94	0.23	0	1	0.81	0.39	0	1
API	Previous year high school Academic Performance Index	534.75	65.82	349.00	679.00	535.99	68.59	349.00	679.00
VC	Previous year violent crime rate(per 1000 persons)	10.65	7.06	0.00	43.90	9.70	8.92	0.00	69.42
PC	Previous year property crime rate(per 1000 persons)	23.26	14.59	0.00	166.02	23.16	13.94	0.00	166.02
Proximity to rail station variables									
B_M400	Binary: 1=0–400 m from mature line Stations	0.03	0.16	0	1	0.01	0.08	0	1
B_M800	Binary: 1=400–800 m from mature line Stations	0.11	0.32	0	1	0.05	0.21	0	1
B_M1600	Binary: 1=800–1600 m from mature line Stations	0.23	0.42	0	1	0.12	0.33	0	1
B_N400	Binary: 1=0–400 m from new line Stations	0.01	0.09	0	1	0.00	0.06	0	1
B_N800	Binary: 1=400–800 m from new line Stations	0.02	0.15	0	1	0.01	0.11	0	1
B_N1600	Binary: 1=800–1600 m from new line Stations	0.05	0.22	0	1	0.04	0.21	0	1
B_P400	Binary: 1=0–400 m from proposed line Stations	0.01	0.09	0	1	0.00	0.07	0	1
B_P800	Binary: 1=400–800 m from proposed line Stations	0.02	0.14	0	1	0.02	0.13	0	1
B_P1600	Binary: 1=800–1600 m from proposed line Stations	0.11	0.31	0	1	0.05	0.22	0	1
HRT	Binary: 1=closer to heavy rail stations	0.43	0.50	0	1	0.31	0.46	0	1
PARKRIDE_400	Binary: 1=Park-and-Ride facilities available within 400 m	0.01	0.09	0	1	0.01	0.08	0	1
PARKRIDE_800	Binary: 1=Park-and-Ride facilities available within 400–800 m	0.05	0.21	0	1	0.04	0.20	0	1
PARKRIDE_1600	Binary: 1=Park-and-Ride facilities available within 800–1600 m	0.23	0.42	0	1	0.12	0.32	0	1

Note: there are no single-family houses within 0–400 m from mature line stations and closer to heavy rail stations in our sample.

included housing physical and neighborhood characteristics as covariates. Our housing physical characteristics included house size, number of bedrooms, number of bathrooms, age of house, lot size and presence of pool. Those features were commonly known to significantly influence housing values and can usually be found on professional real estate listings. Data on neighborhood characteristics, such as school quality, property crime and violent crime, were collected from the city/county of Los Angeles. Based on data from ESRI Inc. and Caltrans, we included proximity variables to highways, railway tracks and bus stops.

3.4. Analytical framework and models

We employed the hedonic pricing model to understand how proximity to rail stations influences property values. Housing prices are determined by a bundle of characteristics. The hedonic pricing model allows us to explicitly test the contribution of certain characteristics (Bartholomew and Ewing, 2011; Rosen, 1974); it is a commonly used method to assess the impact of environmental attributes on property values. In addition to the studies reviewed in Section 2, the hedonic price modeling has been applied to study many other types of housing and environmental attributes (Debrezion et al., 2007; Fuerst and McAllister, 2011; Koschinsky et al., 2012; Mohammad et al., 2013; Saphores and Li, 2012; Zijlstra et al., 2015).

The conceptual model of hedonic analysis is:

$$P = f(D, H, N, e) \tag{1}$$

where P, the sale price of a residential property, is a function of D (proximity to rail stations), H (housing structural characteristics), N (neighborhood characteristics), and e (error term).

Tobler (1970) states the first law of geography as “everything is related to everything else, but near things are more related than distant things”; as briefly mentioned in the literature review section, the prices and characteristics of nearby properties will influence the property being studied. For example, a neighboring house with a beautiful garden would have an additional positive impact over that of a neighboring house without a garden or even with a junkyard. Also, a neighboring house may sell for a higher price due to certain unobserved factors, which would also affect the housing price. On the other hand, asking prices for houses are often the direct product of nearby housing prices (Brasington and Hite, 2005); appraised values for financing are determined by nearby comparable sales (Koschinsky et al., 2012). The spatial dependence effect needs to be effectively controlled for, or it may lead to biased estimates (Koschinsky et al., 2012; Kuethe, 2012; Pace and LeSage, 2008). By performing Moran's I and the Lagrange Multiplier tests, we confirmed the existence of such effects in our model, and chose to employ spatial regression models (Krause and Bitter, 2012; LeSage and Pace, 2009), then compared the results with the OLS regression models. Our main spatial model is the spatial Durbin model (SDM) and we also estimated the Geographically Weighted Regression (GWR) models to check the results' robustness.

3.4.1. Spatial Durbin model

SDM is recommended when the spatial dependence effect exist in both the dependent variable and explanatory variables (LeSage and Pace, 2009). We constructed spatial weight matrices to capture the interactions between each house's price and other characteristics.

Let M, N, and K denote the number of property transactions, the total number of independent variables, and the number of independent variables with spatial lags respectively. Our primary spatial regression model is the spatial Durbin model, written as:

$$\ln(\mathbf{p}) = \rho \cdot \mathbf{W} \cdot \ln(\mathbf{p}) + \mathbf{Z} \cdot \boldsymbol{\beta} + \mathbf{W} \cdot \mathbf{X} \cdot \boldsymbol{\alpha} + \boldsymbol{\varepsilon} \tag{2}$$

where $\ln(\mathbf{p})$ is an M by 1 vector of log-transformed housing prices; ρ is the spatial dependence coefficient; $\mathbf{W}$ is an M by M spatial weight matrix that defines the spatial interactions among houses; $\mathbf{Z}$ is an M by N matrix of independent variables; $\boldsymbol{\beta}$ is an N by 1 vector of coefficients to be estimated; $\mathbf{X}$ is an M by K matrix of independent variables with spatial lags; α is a K*1 vector of spatial lag parameters; and $\boldsymbol{\varepsilon}$ is an M*1 vector of error terms.

The SDM model has two major advantages compared to conventional OLS regression. First, SDM maintains robustness with the omission of relevant independent variables (Ibeas et al., 2012). The spatial lag term on the dependent variable, $\rho \bullet \mathbf{W} \bullet \ln(\mathbf{p})$, controls for the influence of neighboring properties' prices on its own price and incorporates the influence of omitted variables that affect the value of neighboring houses (Brasington and Hite, 2005). Second, the spatial lag term $\mathbf{W} \bullet \mathbf{X} \bullet \boldsymbol{\alpha}$ captures the effects of non-monetary attributes of neighboring properties on property values, for example, the aesthetic characteristics of neighboring properties.

We experimented with three types of spatial weighting matrices in order to understand the structure of spatial dependence among sample properties. The first matrix assigns the same weight to all neighboring observations located within the same Zillow neighborhood boundary and does not permit influences among properties between different neighborhoods. The second matrix is the same as the first matrix, except that it assigns weights to neighboring properties within the same Zillow neighborhood based on the squared inverse distances among the neighboring properties. For the third matrix, we adopted the Delaunay triangulation process that assigns equal weights to neighbors of an observation sharing a Delaunay triangle (LeSage and Pace, 2009). The model estimates with the three matrices are similar, as are the corresponding goodness of fit measures. We chose the Delaunay triangulation matrix as the optimal matrix, because the results from this type of matrix align best with the Geographically Weighted Regression (GWR) model, which is an alternative spatial regression approach we used to check the robustness of SDM results, as introduced in the next section.

3.4.2. Geographically weighted regression

A GWR model takes spatial non-stationarity into account by generating geographically varying parameters and it tackles spatial dependence by incorporating the local spatial relationship into the regression framework. The GWR model consists of a local regression for each housing location based on neighboring properties falling within a certain bandwidth from the location (Saphores and Yeh, 2013). So, each house will have its explicit prices for the explanatory attributes (Fotheringham et al., 2003). The equation for GWR can be written as:

$$\mathrm{P} = \boldsymbol{\beta}_{\boldsymbol{i}} \bullet \boldsymbol{Z} + \mathcal{E}_i \tag{3}$$

where $\boldsymbol{\beta}_{\boldsymbol{i}}$ represents a vector of locally estimated coefficients for the location of observation i, and $\mathcal{E}_i$ is the corresponding error term. $\mathbf{Z}$ is the weighting matrix computed for each observation i and lower weights are placed on observations further away in the estimation for observation i.

Similar to SDM, GWR uses a spatial weighting function to describe the spatial relationship of the target house to nearby houses included in the local regression. The spatial weighting function selects a distance-weighted subsample of neighboring houses to estimate the parameters (LeSage, 2004). The spatial weighting function used in this model is the Gaussian function in the toolbox developed by LeSage (1999) and explained by LeSage (2004). The key inputs in this function are the distance vector between the target house and other houses, the standard deviation of the distance vector, and a decay parameter labeled by Brunsdon et al. (1998) as "bandwidth." The spatial relationship is captured by the ratio between the distance vector and its standard deviation multiplying the bandwidth, which fits into a standard normal density function. By following LeSage (2004), we chose the optimal bandwidth by minimizing the following score function:

$$\sum_{i=1}^{n} [y_i - \hat{y}_{\neq i}(\theta)]^2 \tag{4}$$

where y_i is the observed housing price which is the dependent variable in the model and $\hat{y}_{\neq i}(\theta)$ denotes the predicted housing price using a bandwidth of θ. We selected 0.9345 as the optimal bandwidth, and also ran GWR with alternative bandwidths of 0.5 and 1.5, both of which allowed us to confirm the robustness of the SDM models as well.

4. Results and discussions

We use the spatial econometrics toolbox developed by LeSage and Pace (2010) to estimate the SDM and GWR models. We interpret the results from SDM as the main findings and also present the estimates from GWR. All continuous variables and the dependent variable are log-transformed in those models, so the coefficients of log-transformed variables can be interpreted as elasticity. The coefficients of binary variables can be interpreted as a proportional change.[1]

According to our results, multiple spatial lag variables are statistically significant (see Appendices A and B for detailed OLS and SDM estimation results), indicating that several characteristics of neighboring houses have considerable impact on the target property's value. For instance, the presence of a pool, more bathrooms and larger structural area of neighboring properties are found to positively affect the property value of a house. We found substantial differences between SDM and OLS results. For example, the OLS model reports that being within a quarter mile from a mature rail transit station does not have a significant impact on multi-family property values; but the spatial model confirms that such an impact is significant and its magnitude is 10 times higher than in the OLS estimation. While the OLS model reports a non-significant property value impact for single-family houses located within a quarter mile of a new transit station, the spatial model confirms that such an impact is significant and the magnitude is also much higher than in the OLS estimation. Estimation inconsistencies between the OLS and the SDM are also found on several other variables, such as proximity to highways, rail tracks, and bus stops, as well as crime rates, for both single-family and multi-family housing samples.

We focus on the discussion of SDM results related to the proximity to transit station (summarized in Table 3). All housing physical characteristics have expected signs. The property crime rate has a positive correlation with property values for both single-family houses and multi-family houses; this may be due to the recognized positive association between wealth and property crimes (Bowes and Ihlanfeldt, 2001).

4.1. Property value impact of proximity to rail transit stations

In this section, we compare the SDM estimates from the multi-family and single-family housing samples.

Keeping all other variables constant, the value of an average multi-family property within 400 m of a proposed station is more than twice the value of its counterpart located beyond 1600 m of the station. Such an effect, which is considerably higher than in many previous studies (Mohammad et al., 2013), shows that multi-family houses are associated with a large speculative premium for close proximity to a proposed rail station (Wang et al., 2016). The positive speculative premium is also observed on the other proximity-based variables (400–800 m and 800–1600 m), but is a much smaller magnitude and not statistically significant. On the contrary, we find little speculative premium for the single-family market: all three proximity-based variables have negative signs for the single-family market; e.g. a single-family house located within 400 m to 800 m from a proposed station is 8% (or $42,330) cheaper than its counterpart located at least 1600 m beyond the proposed stations, keeping all other variables constant.

Comparing properties located beyond 1600 m from mature-line stations and keeping all other variables constant, the values of single-family units within 400–800 m of the stations would be significantly lower. On the contrary, the multi-family housing market seems to have reaped substantial benefits by being close to these stations. Multi-family houses located within the three distance bands from mature stations (0–400 m, 400–800 m and 800–1600 m) are 27–99% ($283,090 to $1,030,410) more valuable than their counterparts located beyond 1600 m. However, these capitalization effects decrease considerably when the rail station has a Park-and-Ride available. One possible explanation is that Park-and-Ride facilities are usually associated with several drawbacks. For example, the Park-and-Ride facilities in Los Angeles are mostly bare ground lots which are not pedestrian-friendly. In addition, Park-and-Ride facilities induce more traffic and noise.

Another noteworthy difference between the two housing types is preference toward different rail technology. According to the SDM model, single-family and multi-family residents hold different preferences toward the type of rail transit technology. Heavy-rail transit was appreciated more by single-family residents than by their multi-family counterparts.

We checked the land use and socio-demographic factors in corridors along different rail transit lines and found no substantial differences; with our spatial modeling approach, and controlling for various environment variables, we are confident in making comparisons across different development stages of transit. Our results indicate that the impact of proximity to rail transit stations on single-family property values may not vary across different development stages of the transit systems; generally, the single-family housing market shows little appreciation of rail transit systems during all three stages. On the other hand, the multi-family market showed large speculative appreciation toward the system during the proposed stage, and then as expected by TOD planners, a large premium during the mature stage. However, it is surprising that the multi-family housing market expressed little appreciation toward transit access at the newly open stage.

4.2. Robustness checks of our results

Our SDM models generated global estimates of the premiums for rail transit access. Our GWR results allow us to assess the robustness of the SDM results by exploring the spatial heterogeneity of the premiums (Redfearn, 2009; Weinberger, 2001). Our key GWR results are illustrated in Fig. 2, where the coefficients apply to proximity to rail stations without Park-and-Ride facilities. The estimates of SDM are generally similar to the mean of GWR coefficients (detailed estimates of GWR can be found in Appendices C and D). Such consistency can also be illustrated to some extent in Fig. 2, which shows that the multi-family market appreciates close proximity to the stations at the proposed and mature stages (Red/Purple and Expo lines); the single-family market does not

[1] The proportional change is calculated as $\Delta y = e^{\beta} - 1$, where β is the estimated coefficient.

Table 3.
Property value impact of proximity to rail transit stations: multi-family and single-family markets.

Phase of transit line	Proximity to station	Multi-family houses			Single-family houses		
		SDM coefficients	Compared to those beyond 1600 m (%)	Compared to those beyond 1600 m ($1000)	SDM coefficients	Compared to those beyond 1600 m (%)	Compared to those beyond 1600 m ($1000)
Proposed	0–400 m	**0.7108*****	**103.65%**	**$ 10,720.88**	−0.0822	−7.89%	−$39.86
	400–800 m	0.1437	15.45%	$159.92	**−0.0875***	**−8.38%**	**−$42.33**
	800–1600 m	0.1185	12.58%	$130.21	−0.0451	−4.41%	−$22.28
New	0–400 m	0.1809	19.83%	$205.25	**−0.3074**	**−26.46%**	**−$133.66**
	400–800 m	0.0514	5.27%	$54.55	−0.0984	−9.37%	−$47.33
	800–1600 m	0.0978	10.27%	$106.30	−0.0708	−6.84%	−$34.55
	0–400 m PNR	0.1065	11.25%	$116.40	−0.0991	−9.44%	−$47.69
	400–800 m PNR	0.0231	2.34%	$24.20	0.0616	6.36%	$32.12
	800–1600 m PNR	0.1242	13.23%	$136.97	−0.045	−4.40%	−$22.24
Mature	0–400 m	**0.6909***	**99.55%**	**$1,0300.41**	0.0021	0.21%	$1.06
	400–800 m	**0.3781****	**45.95%**	**$475.61**	**−0.1035***	**−9.83%**	**−$49.66**
	800–1600 m	**0.2418****	**27.35%**	**$283.09**	−0.0458	−4.48%	−$22.63
	0–400 m to HRTS	0.3346	39.77%	$411.62	–	–	–
	400–800 m to HRTS	0.1417	15.23%	$157.68	**0.1993*****	**22.07%**	**$111.49**
	800–1600 m to HRTS	0.0728	7.56%	$78.21	**0.1499*****	**16.18%**	**$81.75**
	0–400 m PNR	0.0177	1.79%	$18.50	−0.0648	−6.28%	−$31.71
	400–800 m PNR	0.0687	7.12%	$73.66	−0.1306	−12.25%	−$61.88
	800–1600 m PNR	-0.0254	-2.51%	−$25.98	−0.0884	−8.47%	−$42.76

Notes: 1) Bold indicates the coefficient is statistically significant at the 0.1(*), 0.05(**) or 0.01(***) level; non-bold coefficients are not significant; estimates are based on Eq. (2). 2) PNR=Park-and-Ride Station, HRTS= Heavy Rail Transit Station. 3) The percentage change, x%, means that, keeping all other variables unchanged, a property located within a particular distance band from a rail station system is x% more valuable than a similar property located beyond 1600 m of the system; the calculation is based on the formula $\Delta y = e^{\beta} - 1$. 4) The property value change in dollar values is calculated based on the average property value in Los Angeles: $1,035,070 for multi-family properties and $505,140 for single-family properties.

appreciate close proximity to these lines.

The spatial variation patterns illustrated in Fig. 2 further prove that preferences toward transit accessibility differentiates among various corridors. We do not have a comprehensive explanation for the spatial variation of coefficients illustrated in Fig. 2; the variation may be due to the complex urban housing market and heterogeneous built environment features. For example, people's willingness to pay for access to a transit station may be moderated depending on the safety and built-environment features around the stations.

4.3. Comparison with previous studies

Previous studies relying on conventional OLS regressions mostly claim positive price premiums for single-family properties near transit stations. Our study raises a concern about the accuracy of such studies due to the lack of control for the spatial dependence effect. However, some previous studies report negative impacts (Debrezion et al., 2007) for the single-family market. For example, Bowes and Ihlanfeldt (2001) found that single-family houses within a quarter mile from stations in Atlanta sold for 19% less than houses beyond three miles. Mohammad et al. (2013) have indicated that people are willing to pay more for a transit system if they live in a place with a higher transit mode share. Our findings also show that residents from single-family households in an auto-oriented city might not perceive transit systems as a positive amenity; however, multi-family households in Los Angeles seem to place a positive value on transit accessibility.

Our findings also agree with some previous studies that properties near Walk-and-Ride stations have greater capitalization benefits than those near Park-and-Ride stations (Atkinson-Palombo, 2010; Billings, 2011; Bollinger and Ihlanfeldt, 1997; Gatzlaff and Smith, 1993; Kahn, 2007). In addition, our findings agree with certain previous studies that the transit system is capitalized very differently between single-family houses and other housing markets (Atkinson-Palombo, 2010).

5. Conclusions and policy implications

Our answers to the study's research questions are summarized as follows. First, our spatial regression models mitigate the threat of the spatial dependence effect and achieve higher estimation accuracy compared to the Ordinary Least Squares regression. Second, proximity to rail transit stations generally does not benefit single-family property values, while the multi-family market greatly appreciates close proximity to transit stations. The premium for proximity to rail transit stations may also vary by different development stages and rail technologies. Further, station-area land use may drastically moderate the premium for station access: stations with Park-and-Ride facilities generally do not benefit property values nearby.

The conflict between automobile popularity and urban sustainable development urges transportation planners to rethink urban transportation strategies; many consider public transit to be a panacea. The trends of economic growth and decentralization of jobs and residence require the recognition of a broader set of criteria rather than simply and naively denying or advocating one policy (Bouf and Hensher, 2007; Hensher, 2007). Our findings

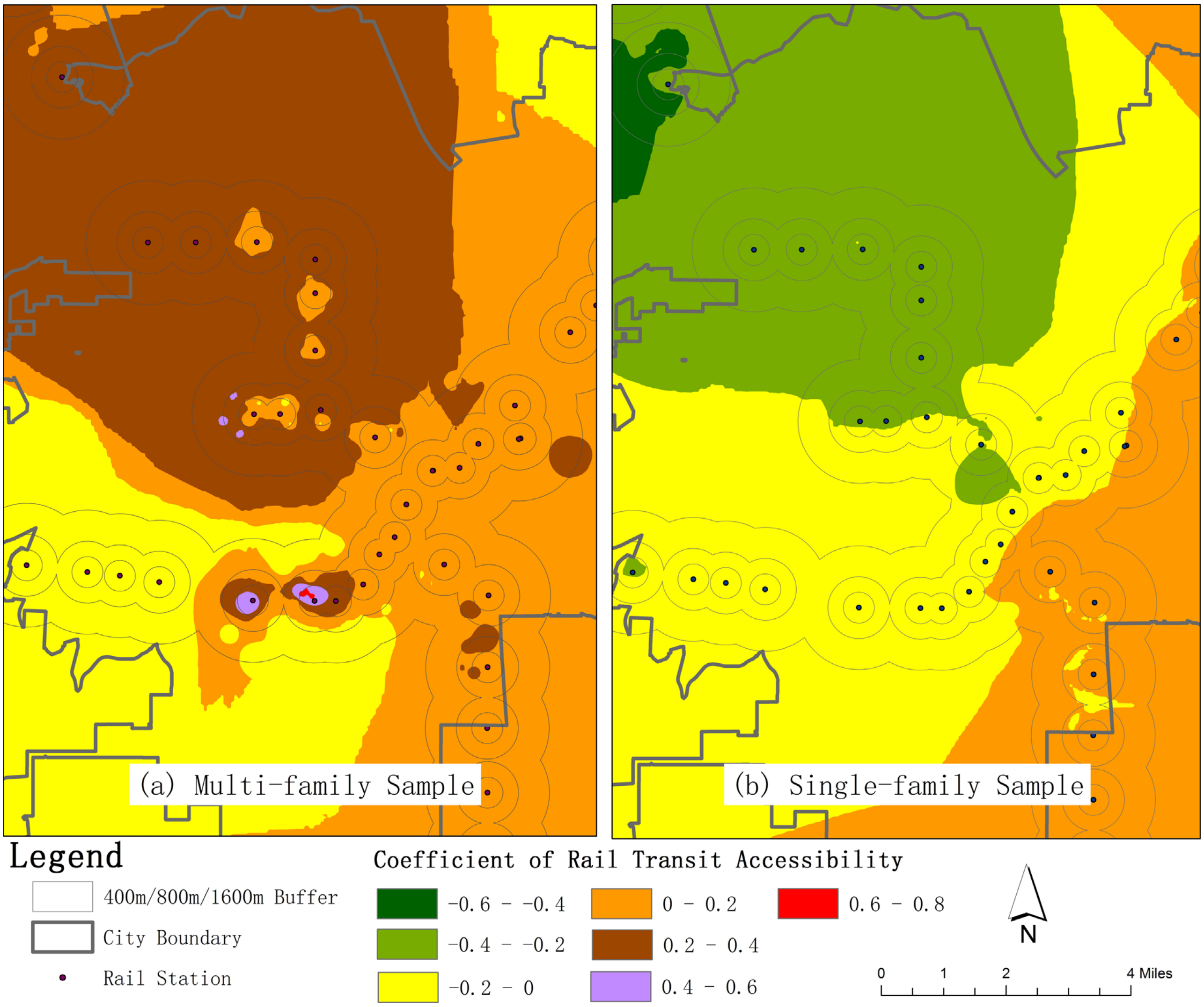


Fig. 2. Distribution of premiums for transit accessibility based on GWR models. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

contribute to the relevant policy debate by affording the following policy implications.

First, the property value effects should be taken into consideration when determining the placement of Park-and-Ride facilities. Previous literature regarding the placement of Park-and-Ride facilities mainly focused on factors such as VMT reduction, coverage maximization, accessibility, and parking demand (Faghri et al., 2002; Kok et al., 1994; Spillar, 1997). However, this study shows that the existence of Park-and-Ride facilities greatly compromises the property value benefit of transit stations. Transport policy makers should pay attention to residents' preferences and concerns toward these facilities, which provide transit access to residents across the city but impose negative outcomes on those living nearby.

Previous studies have found the provision of Park-and-Ride facilities to be controversial (Kuby et al., 2004; Meek, 2008; Zijlstra et al., 2015). While Park-and-Ride may effectively attract more riders by making mass transit feasible for those who do not live in the vicinity of stations, it also may shift people from walking or biking to transit stations to driving to transit stations (Mingardo, 2013). Park-and-Ride facilities are also associated with financial cost (Duncan and Christensen, 2013), diminished quality of pedestrian environment (Hess et al., 1999), deterrent to TOD (Duncan and Christensen, 2013), and increased vehicle miles traveled (VMT)(Meek et al., 2011). Most of these negative effects contradict the long-term objectives of TOD, so the provision of Park-and-Ride for the sake of ridership is not a justifiable policy option. For example, instead of relying on Park-and-Ride to reduce VMT, improved bus service to provide seamless origin-destination trips may potentially work better (Hensher, 2007). The tension between providing parking space at rail stations and encouraging TOD has been investigated by Duncan, (2010b), Willson and Menotti, (2007), but they did not connect the tradeoffs of the two policy options to the parking replacement decisions of transit agencies (Duncan and Christensen, 2013).

Park-and-Ride facilities occupy large amounts of land and impede pedestrian-oriented development (Mathur and Ferrell, 2009). The question that arises here is whether and how to offset the negative effects of Park-and-Ride through better design of the facilities and the station-area land use. How Park-and-Ride facilities are built could partly influence the premiums for transit accessibility. O'Sullivan and Morrall (1996) indicated that people in suburban locations would walk to stations if the built environment were pedestrian-oriented. Providing pedestrian-oriented environments could encourage more people to use LRT in suburbia, too.

Second, better built environment and diverse housing options around transit-station areas requires upzoning. Taking the provision of Park-and-Ride facilities as an example, one possible design of Park-and-Ride or parking provision could be on-street or multi-level parking integrated with other uses, such as department stores and other retail shops in multi-floor buildings. Such a design brings potential opportunities to improve the pedestrian environment and encourages employees to take public transit. The strategy converts the Park-and-Ride lots to Park-Ride-Work-and-Consume complexes. Employers would benefit from the robust economic activities and transportation supply (Schuetz, 2015; Weisbrod et al., 2014). Then, employers might provide incentives to encourage employees to take transit (Enoch and Potter, 2003). Another upzoning example would be to add more multi-family residential units. This study finds that multi-family houses benefit from transit access in terms of property values much more than do single-family houses. Additional multi-family units contribute to increased residential density, which is consistent with the long-term interest of TOD, namely, greenhouse gas reduction, congestion mitigation, and health promotion (Chatman, 2013).

Finally, because the premium for transit access may be volatile, depending on various factors, we do not recommend equal-rate value capture policies for financing rail transit infrastructure. In accordance with certain studies, our results of spatial variation suggest that price effects for close proximity to stations are not global (Du and Mulley, 2012; Mulley, 2014; Redfearn, 2009) and they depend on several factors such as property type and land use patterns. Gathering value-capture taxes throughout a new transit corridor at the same rate is therefore not justified. In addition, some Park-and-Ride stations have become magnets that attract the poor to live nearby (Kahn, 2007; Krause and Bitter, 2012). Our results indicate that the low income population may indeed be attracted to Park-and-Ride stations due to lower housing prices. The actual users would be the motorists who live further away rather than the people living nearby. Fortunately, cities have tried to finance transit development in ways other than value capture, such as sales taxes in Los Angeles (CA) and Denver (CO), petroleum business taxes in New York City (NY), and commercial real estate taxes in Arlington (VA). Our results suggest a possible speculation on the properties before the rail line is in operation. The cities that decide to implement value capture measures should conduct comprehensive studies and adopt sophisticated models to allow them to understand the heterogeneous premiums for transit access depending on factors such as property markets and near-station land use. Our results show that the impacts vary distinctly by whether Park-and-Ride facilities are available.

Furthermore, a phase-specific value capture could be applied too. Agostini and Palmucci (2008) suggest that the increased property tax collection after reappraisal could be used to finance rail transit investment, when anticipated capitalization occurs. However, our study is consistent with Wang et al. (2016), who argues that the speculative premiums in prices may not equal the prices that people are willing to pay for rail transit service. We find that the multi-family market sees a high speculative premium during the proposed stage. It is possible that the anticipated property value increase for the multi-family market is greater than the actual increase when the system opens and land use around it matures. According to the value capture principle, a public authority should capture the financial benefits generated by public investment. As the speculative premium may be short-term and unstable, it is necessary to assess the value capture taxes based on the actual property value impact after the system becomes mature. We suggest that transit authorities carry out a hedonic analysis regularly and monitor changes in the premiums for transit access. These measures could help policy makers better understand residents' preferences concerning transit access, as well as help them safeguard equity when assessing value capture taxes.

Acknowledgement

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Appendix A

See Table A1 here.

Table A1.
Comparing OLS and SDM results: multi-family sample.

	OLS		SDM			
Variables	Coefficient	Standard error	Coefficient (direct effect)	Inferred standard Error	Mean of total effect	Standard deviation
LOG_PAREA	0.0858*	0.0512	0.1170**	0.0482	0.1070	0.0010
LOG_SAREA	0.4489***	0.063	0.4009***	0.0600	0.4187	0.0018
LOG_UNIT	0.2545***	0.0832	0.2749***	0.0784	0.2673	0.0008
LOG_BATHRM	0.0741	0.0775	0.0169	0.0720	0.0424	0.0026
LOG_BEDRM	0.0852	0.0625	0.1291**	0.0591	0.1173	0.0012
B_POOL	−0.0369	0.0674	−0.0298	0.0642	0.0284	0.0001
LOG_AGE	−0.2604	0.1795	−0.3413**	0.1661	−0.3506	0.0009
LOG_AGE2	0.0205	0.0253	0.0302	0.0235	0.0313	0.0001
B_PARK	0.0226	0.0532	0.0107	0.0535	0.0108	0.0000
B_SPRMK	0.0044	0.0397	0.0042	0.0379	0.0043	0.0000
B_MSM	0.0777	0.1055	0.0416	0.1022	0.0422	0.0001
B_HWY	−0.0732**	0.037	−0.0563	0.0374	−0.0571	0.0001
B_RAIL	−0.1725***	0.0579	−0.1647***	0.0573	−0.1669	0.0002
B_PWRLN	0.0041	0.0443	−0.0116	0.0454	−0.0118	0.0000
B_LNDFL	−0.1556***	0.0479	−0.1232**	0.0550	−0.1248	0.0002
B_BUS	−0.1288**	0.0611	−0.0578	0.0656	−0.0586	0.0001
LOG_API	0.4212***	0.1261	0.3639**	0.1422	0.3688	0.0005
LOG_VC	−0.1914***	0.0279	−0.1401***	0.0308	−0.1420	0.0002
LOG_PC	0.1518***	0.0332	0.0928***	0.0359	0.0940	0.0001

Table A1. (*continued*)

	OLS		SDM			
Variables	Coefficient	Standard error	Coefficient (direct effect)	Inferred standard Error	Mean of total effect	Standard deviation
B_M400	0.0531	0.3268	0.6909*	0.3621	0.6277	0.0065
B_M800	0.2152*	0.1105	0.3781**	0.1569	0.3772	0.0001
B_M1600	0.0540	0.0721	0.2418**	0.1198	0.2377	0.0004
B_N400	0.1648	0.1722	0.1809	0.2617	0.1994	0.0019
B_N800	0.0115	0.1034	0.0514	0.1948	0.0452	0.0006
B_N1600	-0.0367	0.1097	0.0978	0.1581	0.0896	0.0008
B_P400	0.6337***	0.1617	0.7108***	0.2221	0.7267	0.0016
B_P800	0.0055	0.1044	0.1437	0.1476	0.1413	0.0003
B_P1600	−0.0631	0.0448	0.1185	0.0851	0.1045	0.0014
HRT_M400	0.0997	0.3157	−0.3563	0.3321	−0.3038	0.0054
HRT_M800	−0.1644	0.1149	−0.2364	0.1695	−0.2459	0.0010
HRT_M1600	0.0465	0.0705	−0.1690	0.1220	−0.1625	0.0007
M400_PARKRIDE	−0.1533	0.2526	−0.6732**	0.2796	−0.6592	0.0014
M800_PARKRIDE	0.0844	0.0854	−0.3094**	0.1255	−0.2798	0.0030
M1600_PARKRIDE	−0.0009	0.0578	−0.2672***	0.0866	−0.2549	0.0013
N400_PARKRIDE	0.0228	0.4431	−0.0744	0.4630	−0.1142	0.0041
N800_PARKRIDE	−0.1992	0.2343	−0.0283	0.2844	−0.0033	0.0026
N1600_PARKRIDE	−0.0373	0.1312	0.0264	0.1777	0.0230	0.0003
W_LOG_PAREA			−0.2297**	0.1085		
W_LOG_SAREA			0.2486**	0.1264		
W_LOG_UNIT			−0.2240	0.1913		
W_LOG_BATHRM			0.5031***	0.1857		
W_LOG_BEDRM			−0.2691*	0.1504		
W_B_POOL			−0.0366	0.1479		
W_LOG_AGE			−0.0934	0.3131		
W_LOG_AGE2			0.0147	0.0450		
W_B_M400			−1.4453*	0.7989		
W_B_M800			−0.1196	0.2811		
W_B_M1600			−0.1465	0.1834		
W_B_N400			0.3201	0.4632		
W_B_N800			−0.1377	0.2770		
W_B_N1600			−0.1900	0.2710		
W_B_P400			0.1279	0.3684		
W_B_P800			−0.0872	0.2598		
W_B_P1600			−0.3116***	0.1135		
W_HRT_M400			1.1421	0.7628		
W_HRT_M800			−0.1260	0.2874		
W_HRT_M1600			0.1757	0.1817		
W_M400_PARKRIDE			0.4590	0.6199		
W_M800_PARKRIDE			0.6732***	0.2127		
W_M1600_PARKRIDE			0.3167**	0.1260		
W_N400_PARKRIDE			−0.7745	1.3514		
W_N800_PARKRIDE			0.5067	0.4978		
W_N1600_PARKRIDE			−0.0747	0.3299		
Intercept	0.4664	0.9102	0.9621	0.9862		
rho			0.2670***	0.0575		
Adjusted R-squared	0.6636		0.6875			
RMSE			0.3612			
MAE			0.2518			

Note: 1) The direct effects are coefficients that are directly estimated from the spatial model; the total effect is the combination of the direct effect and the “indirect” effect that arises due to the spatial dependence effect; the total effect may vary from one observation to another due to the incorporation of the spatial weight matrix in the calculation. In our case, the total effect and the direct effect is similar; 2)*, ** and *** represent significance levels of 0.1, 0.05 and 0.01 respectively. 3) RMSE stands for the Root-Mean-Square Error and MAE stands for the Mean Absolute Error.

Appendix B

See Appendix Table B1.

Table B1.
Ordinary least square model and spatial Durbin model comparison: single-family houses.

	OLS		SDM			
Variables	Coefficient	Standard error	Coefficient (direct effect)	Inferred standard error	Mean of total effect	Standard deviation
LOG_PAREA	0.1322***	0.0097	0.1166***	0.0090	0.1119	0.0005
LOG_SAREA	0.6765***	0.0143	0.4626***	0.0137	0.5292	0.0073
LOG_BATHRM	0.0688***	0.0111	0.0637***	0.0098	0.1052	0.0046
LOG_BEDRM	−0.1522***	0.0127	−0.0420***	0.0115	−0.0630	0.0023
B_POOL	0.1380***	0.0124	0.1234***	0.0110	0.1561	0.0036

Table B1. (*continued*)

	OLS		SDM			
Variables	Coefficient	Standard error	Coefficient (direct effect)	Inferred standard error	Mean of total effect	Standard deviation
LOG_AGE	−0.0382	0.0295	−0.1091***	0.0264	−0.1310	0.0024
LOG_AGE2	0.0083*	0.0046	0.0147***	0.0042	0.0175	0.0003
B_PARK	−0.0237*	0.0125	−0.0059	0.0144	−0.0065	0.0001
B_SPRMK	−0.0796***	0.0178	−0.0549***	0.0181	−0.0601	0.0006
B_MSM	0.0493	0.0529	0.0335	0.0535	0.0367	0.0004
B_HWY	−0.0755***	0.0104	−0.0452***	0.0129	−0.0495	0.0005
B_RAIL	−0.0700***	0.0125	−0.0434***	0.0154	−0.0475	0.0005
B_PWRLN	0.0119	0.0099	0.0034	0.0135	0.0037	0.0000
B_LNDFL	−0.1399***	0.0103	−0.1372***	0.0169	−0.1502	0.0014
B_BUS	−0.1584***	0.0092	−0.1083***	0.0135	−0.1186	0.0011
LOG_API	0.8896***	0.0315	0.8123***	0.0506	0.8895	0.0085
LOG_VC	−0.1958***	0.0057	−0.1179***	0.0079	−0.1291	0.0012
LOG_PC	0.1696***	0.0074	0.0936***	0.0095	0.1025	0.0010
B_M400	−0.0119	0.0614	0.0021	0.0868	−0.0006	0.0003
B_M800	−0.1180***	0.0315	−0.1035*	0.0595	−0.1276	0.0027
B_M1600	−0.0891***	0.0209	−0.0458	0.0449	−0.0732	0.0030
B_N400	−0.0800	0.0615	−0.3074**	0.1208	−0.2891	0.0020
B_N800	0.0005	0.0345	−0.0984	0.0702	−0.0949	0.0004
B_N1600	−0.0868***	0.0191	−0.0708	0.0467	−0.0802	0.0010
B_P400	−0.1072**	0.0458	−0.0822	0.0742	−0.1091	0.0030
B_P800	−0.0761***	0.0253	−0.0875*	0.0526	−0.0981	0.0012
B_P1600	−0.0340**	0.0149	−0.0451	0.0333	−0.0494	0.0005
HRT_M800	0.2986***	0.0349	0.3028***	0.0652	0.3457	0.0047
HRT_M1600	0.2984***	0.0204	0.1957***	0.0463	0.2448	0.0054
M400_PARKRIDE	−0.0529	0.0787	−0.0669	0.1086	−0.0878	0.0023
M800_PARKRIDE	−0.0650*	0.0335	−0.0271	0.0613	−0.0421	0.0017
M1600_PARKRIDE	−0.0791***	0.0192	−0.0426	0.0399	−0.0503	0.0008
N400_PARKRIDE	0.0701	0.1349	0.2083	0.2073	0.2048	0.0004
N800_PARKRIDE	−0.0688	0.0698	0.1600	0.1356	0.1264	0.0037
N1600_PARKRIDE	−0.0058	0.0335	0.0258	0.0669	0.0219	0.0004
W_LOG_PAREA			−0.1022***	0.0217		
W_LOG_SAREA			0.1469***	0.0272		
W_LOG_BATHRM			0.2305***	0.0265		
W_LOG_BEDRM			−0.1106***	0.0304		
W_B_POOL			0.1363***	0.0302		
W_LOG_AGE			−0.0748	0.0658		
W_LOG_AGE2			0.0092	0.0103		
W_B_M400			−0.0188	0.1493		
W_B_M800			−0.0927	0.0840		
W_B_M1600			−0.1500**	0.0596		
W_B_N400			0.3082*	0.1703		
W_B_N800			0.0833	0.0969		
W_B_N1600			−0.0174	0.0578		
W_B_P400			−0.1238	0.1153		
W_B_P800			−0.0148	0.0710		
W_B_P1600			0.0000	0.0000		
W_HRT_M800			0.0916	0.0932		
W_HRT_M1600			0.1978***	0.0597		
W_M400_PARKRIDE			−0.0945	0.1927		
W_M800_PARKRIDE			−0.0807	0.0893		
W_M1600_PARKRIDE			−0.0238	0.0542		
W_N400_PARKRIDE			−0.1511	0.3648		
W_N800_PARKRIDE			−0.3172	0.1982		
W_N1600_PARKRIDE			−0.0410	0.0921		
Intercept	−5.7324***	0.2293	−3.4626***	0.3327		
rho			0.6170***	0.0125		
Adjusted R-squared	0.7571		0.7747			
RMSE			0.3649			
MAE			0.2536			

Note: 1) The direct effects are coefficients that are directly estimated from the spatial model; the total effect is the combination of the direct effect and the "indirect" effect that arises due to the spatial dependence effect; the total effect may vary from one observation to another due to the incorporation of the spatial weight matrix in the calculation. In our case, the total effect and the direct effect is similar; 2)*,** and *** represent significance levels of 0.1, 0.05 and 0.01 respectively. 3) RMSE stands for the Root-Mean-Square Error and MAE stands for the Mean Absolute Error.

Appendix C. Distribution of GWR coefficients: multi-family sample

See Fig. C.

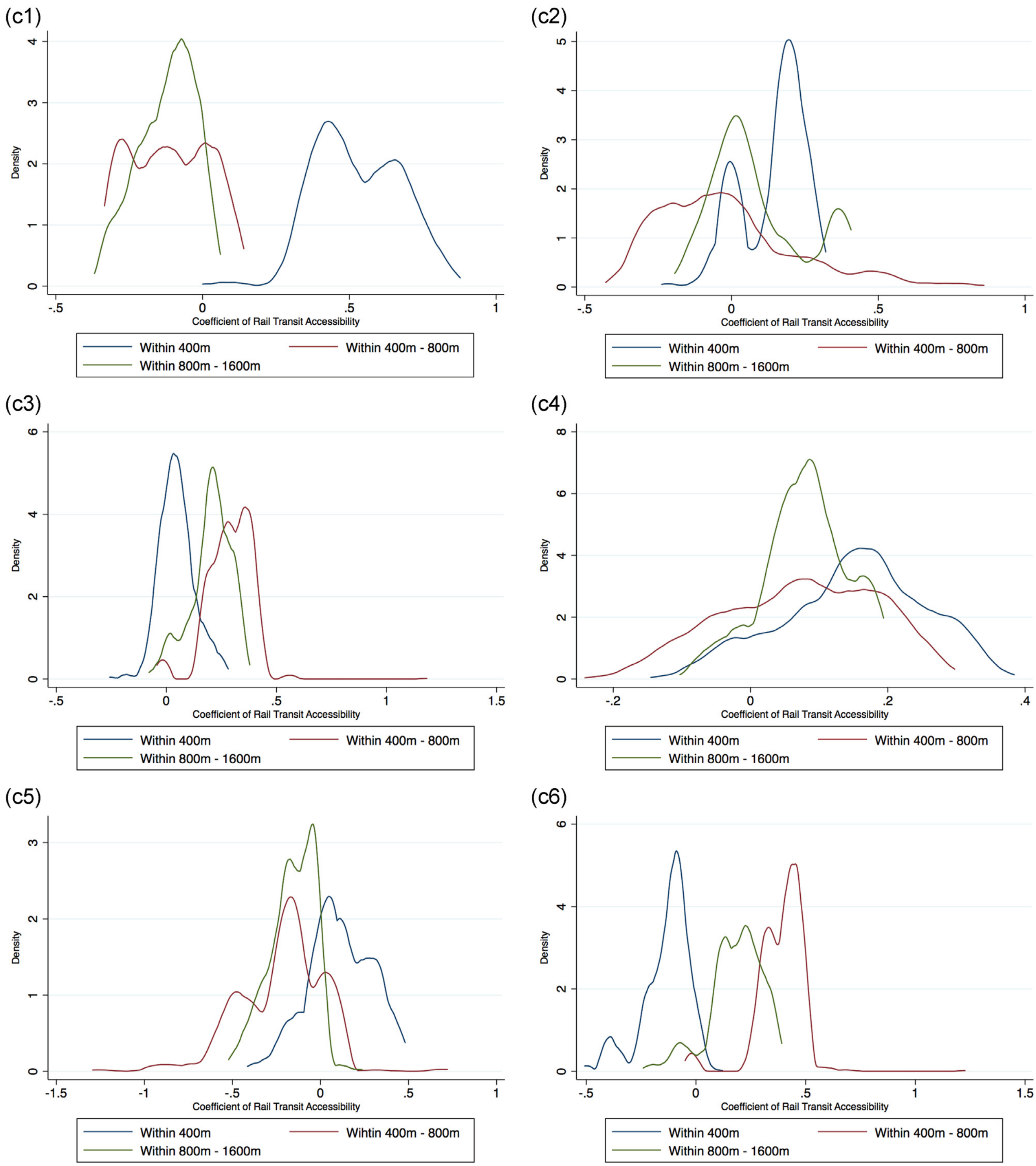

Fig. C. Fig. C1 Proximity to proposed light rail stations without Park-and-Ride facilities; Fig. C2 proximity to new opening light rail stations without Park-and-Ride facilities; Fig. C3 proximity to mature light rail stations without Park-and-Ride facilities; Fig. C4 proximity to heavy rail stations without Park-and-Ride facilities; Fig. C5 proximity to new opening light rail stations with Park-and-Ride facilities; Fig. C6 proximity to mature light rail stations with Park-and-Ride facilities.

Appendix D. : Distribution of GWR coefficients: single-family sample

See Fig. D.

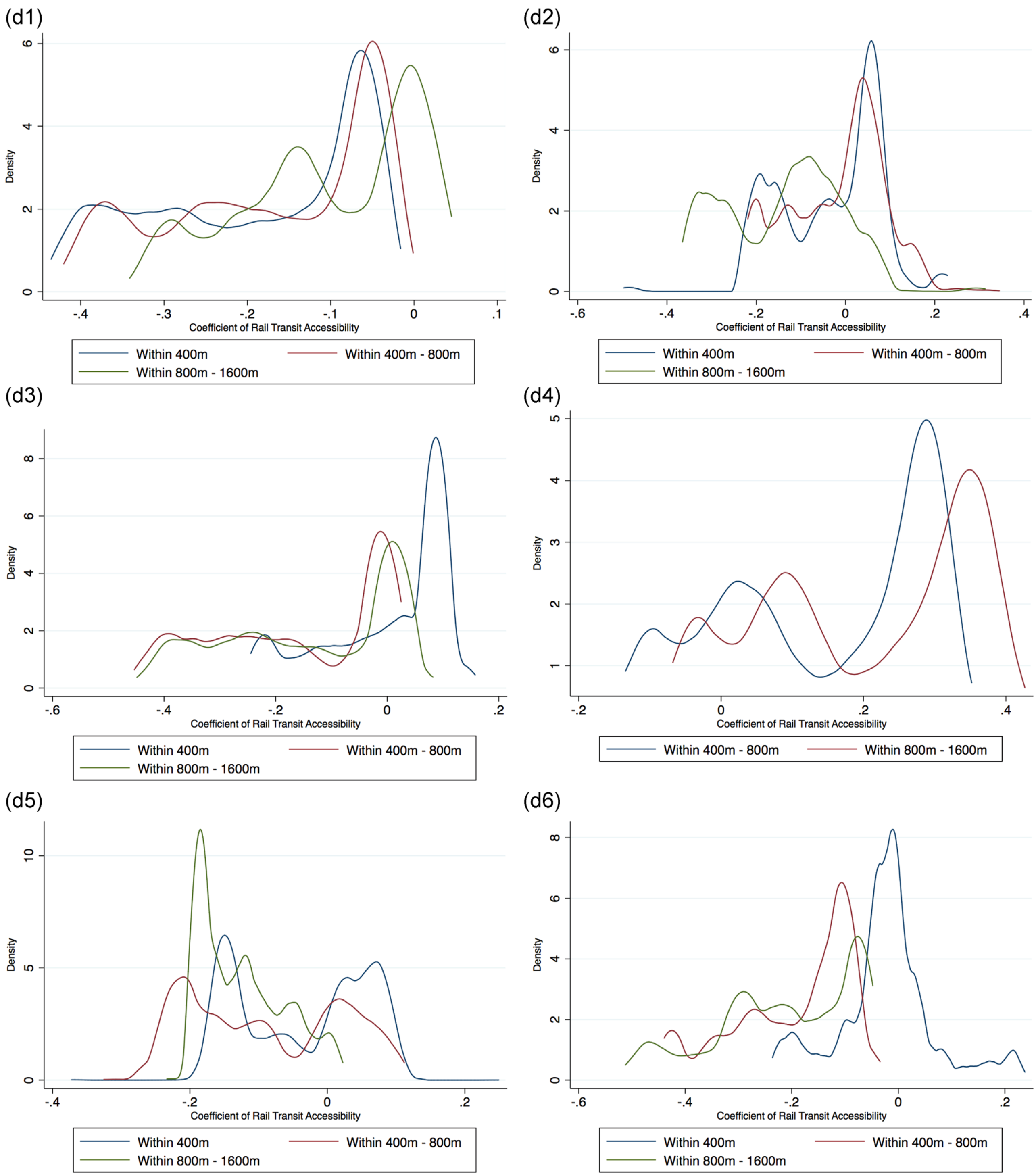

Fig. D. Fig. D1 Proximity to proposed light rail stations without Park-and-Ride facilities; Fig. D2 proximity to new opening light rail stations without Park-and-Ride facilities; Fig. D3 proximity to mature light rail stations without Park-and-Ride facilities; Fig. D4 proximity to heavy rail stations without Park-and-Ride facilities; Fig. D5 proximity to new opening light rail stations with Park-and-Ride facilities; Fig. D6 proximity to mature light rail stations with Park-and-Ride facilities; Note: no observations located within 400 m to heavy rail stations, so no distribution of within 400 m in Fig. D4.

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