If We Build, Will They Pay? Predicting Property Price Effects of Transport Innovations

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Abstract

In this study I develop a partial equilibrium approach for the prediction of property price effects of transport network extensions. It combines a gravity-type labor market accessibility indicator with a transport decision model that takes into account the urban rail network architecture, allows for mode switching and relaxes the assumption that stations represent perfect substitutes. The model is calibrated to the Greater London Area and is used to predict property price effects of the 1999 Jubilee Line and DLR extension. A considerable degree of heterogeneity is predicted both in terms of the magnitude as well as the spatial extent of price effects around new stations. A quasi-experimental property price analysis reveals that the model performs well in predicting the observed average accessibility effect. Relative transport costs associated with distinct transport modes are identified from the data by calibrating the model of observed property price adjustments.

1 Introduction

Transport infrastructure projects are among the largest public expenditure programs worldwide. As an example, costs for implementing a high speed rail network in Britain, which mainly consists of a Y-shaped connection of London to Birmingham, Leeds and Manchester of about 500 km length are scheduled to reach as much as £34 billion at present (UK Department for Transport, 2010). Similarly ambitious projects are evaluated in many parts of the world, not least in the U.S. where optimistic scenarios encompass efforts to develop a high speed rail network that is comparable to the interstate highway program of the 20th century (US Department of Transportation, 2009). Often, the most expensive parts of new rail networks are the downtown sections of heavy rail systems as they have to be developed into densely developed cities where the opportunity cost of land are high, if not entirely underground. Crossrail, a new major high capacity rail line

crossing the Greater London Area in the East-West direction along a 22km tunnel section, is currently estimated to come to a total cost of about £15 billion.

These huge costs are counterbalanced by similarly large potential public and private benefits, which are typically assessed in social-cost-benefit analyses. In addition to the monetary equivalent to travel time savings incurred by users, indirect effects might be derived from various forms of agglomeration economies, i.e. localization or urbanization economies due to enhanced interactions among businesses, improved labor market matching or improved access to intermediate inputs. Still the question of how to finance and recover huge public expenditures remains open in practice. Increasingly, compensations from property owners who receive an external benefit from publicly funded transport projects have been discussed as a potential source of revenue. Furthermore, increases in property values naturally induce property tax revenues. Thus there is a substantial public interest in property price effects of transport improvements, which could be considered in viability studies.

Property price effects of transport infrastructure have received considerable attention in the academic literature. Amongst other reasons because, following bid-rent theory, land values and property prices should mirror any increase in productivity or household utility related to accessibility and thus qualify as a natural starting point of a welfare analysis of economic effects of transport infrastructure. By and large, property price effects of transport infrastructure and in particular urban rail systems are well-documented (e.g. Ahlfeldt & Wendland, 2010a; Bajic, 1983; Baum-Snow & Kahn, 2000; Bowes & Ihlanfeldt, 2001; Damm, Lerner-Lam, & Young, 1980; Dewees, 1976; Gatzlaff & Smith, 1993; McDonald & Osuji, 1995; Voith, 1993). Debrezion, Pels, and Rietveld (2007) provide a meta-analysis on this strand of research. It has, however, proven to be a challenge to separate the pure accessibility effect from correlated location effects as there might be sorting of households and firms with respect to infrastructure and their location might be jointly determined with other (unobserved) location features. The recent literature has, therefore, moved on to investigate the property price effects of transport innovations over time so that unobserved (time-invariant) location characteristics can be held constant and the true accessibility effects better isolated (e.g. Ahlfeldt, 2010b; Ahlfeldt & Wendland, 2009; Gibbons & Machin, 2005; McMillen & McDonald, 2004).

Still, and despite the public interest, it remains difficult to predict property price effects for scheduled transport innovations as the existing literature mainly provides case-based evidence on average treatment effects, e.g. marginal price effects of rail station proximity. Stations, thereby, are implicitly treated as perfect substitutes at the expense of ignoring their position within a network hierarchy as well as their centrality in an urban system, let alone the role of alternative transport modes and effects that spread along preexisting parts of the network. With this contribution I aim to fill this gap and develop a partial equilibrium approach that overcomes the aforementioned limitations and can be used to predict property price effects of transport innovations while at the same time remaining as simple as possible to facilitate straightforward applications.

This approach makes use of three basic ingredients. First, I build on a recent strand in empirical urban economics research where gravity-type variables are used to link the attractiveness of locations to all other places within an urban area or region so that the role of labor market accessibility can be evaluated within an environment of dispersed employment (Ahlfeldt, 2010a; Osland & Thorsen, 2008). Second, I develop a simple transport decision model that allows modeling the transport costs incurred in from of travel time between any pair of location in the presence of competing transport modes. Changes in the urban travel cost matrix can thus be used to predict the effect of transport innovations based on parameters that can be estimated before the innovation actually takes place. Third, I set up a transport innovation model in the spirit of Gibbons & Machin (2005) (henceforth GM) to evaluate the predictive power of the gravity accessibility model. The time dimension is then used to calibrate the model to observed property market reactions and to back out the relative transport costs of competing transport modes, which is achieved in an extensive sensitivity analysis.

I chose the 1999 extension of the London Underground (LU) Jubilee Line and Docklands Light Railway (DLR) network as a case in point for mainly two reasons. First, it represents an interesting case for the prediction exercise as the extension was substantial, on the one hand, but small enough relative to the overall transport network to justify a partial equilibrium approach on the other. It has provided improved access to a major employment sub-center (Canary-Warf) as well as the traditional CBD, especially along the central fraction of the Jubilee Line extension. Moreover, some stations were introduced into an area where a relatively dense network was already present while others represented an exten-

sion into residential areas that were not previously accessible by the LU or DLR. Thus, I expect considerable heterogeneity in the model predictions in terms of both magnitude and the spatial extent of price effects. Second, this extension has been analyzed by GM in one of the most careful property market analyses of transport innovations available in the literature. Their results qualify as the natural benchmark for an evaluation of the predictive power of the model and the added value of incorporating a more sophisticated modeling of accessibility more generally. While in this setup, the effects of urban rail transport on residential property prices are studied, I note that, given the availability of appropriate data, the same approach could also be applied to other transport modes and non-residential property.

The empirical analyses in this paper can be categorized into two major stages. After a brief introduction into the data and the institutional settings in Section 2, I estimate a gravity accessibility model for the Greater London area prior to the considered network extension. With the estimated parameters I predict the property effects based on the change in the network architecture and evaluate the predictions with respect to GM's findings. These analyses in Section 3 are mainly of a cross-sectional nature and require somewhat arbitrary assumptions regarding the relative transport cost of distinct transport modes. I take the analysis a step further in Section 4 to incorporate the observable changes in property prices and make explicit use of the time dimension. While considerably extending the observation period, I try to remain conceptionally close to GM's transport innovations model to not only compare the predictive power of the model to the observed market reactions but also to their more conventional treatment indicator. This set up will be used to conduct a sensitivity analysis of the model predictions with respect to the assumed relative transport costs associated with distinct transport modes. Thereby, it is possible to back out the parameters that bring predicted and observable changes in property prices closest together. Previewing my results, the last section concludes that the model predictions do well in explaining observable property market reactions and that, within a reasonable range, the model is not too sensitive with respect to the assumptions regarding the relative transport cost parameters.

2 Data & Background

The property data used in this study is provided by the Nationwide Building Society. This well-established data set identifies the transaction price of residential properties and a range of transaction characteristics. The Nationwide data set covers most of the property characteristics that are common in the hedonic literature. The main difference to the study by GM is that I use an extended period ranging from January 1995 to July 2008 (as opposed to 1997–2002). For each property transaction, a spatial reference is provided in the form of the full postcode, which is a relatively high spatial detail. Within the Greater London Authority, which defines the study area, there are close to 168,000 postcode units. A typical postcode will encompass about 10-15 households. This spatial reference facilitates merging individual transactions with other data in a GIS environment. Location and environmental control variables could thus be generated based on electronic maps or merged from other sources. Such important sources include the national pupil database, from which postcode level KS2 results could be obtained and the 2001 census, which features several characteristics at output area level. As in the previous study by GM, I strictly refer to the geographic centroid of a postcode as the spatial reference for all transactions that fall into the respective unit.

While the data processing is straightforward for most of the variables, some words are due on the school quality indicator based on key-stage 2 (KS2) test scores. Due to confidentiality restrictions, I obtained a data set which is limited to output areas with at least three registered pupils in the period from 2002 to 2007. I assume that school quality can be approximated by the average KS2 test score of pupils in the neighborhood, where pupils living nearby should receive higher weights as the likelihood of pupils' attending one school decreases in distance. Based on these assumptions, a postcode level school quality indicator can be approximated based on a spatial interpolation of average output area test scores, which also fills a limited number of gaps that result from confidentiality restrictions.[1] The other variables included in a vector of *location controls,* which I will refer to in several Tables, include the distance to the nearest historic house, landmark, museum or religious site, the shortest distance to the national rail network, an indicator variable for

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[1] Precisely, I use ordinary kriging based on a spherical semi-variogram model to interpolate between output area centroids and to generate an auxiliary grid, to which I assign postcodes based on their geographic centroids.

postcodes within 500m of a major road and a similar variable for a 500m distance band around rivers, canals and lakes, a combined air quality index and the percentage of whites at the whole (output area) population.

For the reasons discussed above, I focus on the same transport innovation as GM, the 1999 LU Jubilee Line and DLR extension. Both extensions took place in the south-east London area, which was previously relatively poorly connected. The new sections of the Jubilee Line extend the pre-existing line from Westminster in Central London, south to the River Thames to the major employment sub-center at Canary Wharf and then to Stratford, the site where the main campus of the 2012 Olympics will be located. With a total project cost of about £3.5 billion for about a roughly 16 km extension, GM consider this project the most significant change in the London Underground network for 30 years. In comparison, the DLR extension that took place in the same year is of more moderate dimensions. The light railway network was extended by about 4.3 km and five new stations towards Lewisham, crossing the River Thames underground. The new sections are depicted in Figure 2. For further detail on the data and institutional background I refer to GM.

3 Calibration & Prediction

3.1 Empirical Strategy

There is a tradition of using gravity variables to empirically describe accessibility patterns in the urban and housing literature (e.g. Cervero, 2001; Cervero, Rood, & Appleyard, 1999; Wang & Minor, 2002), but their application in the house price capitalization literature has not gained much pace until recently (Adair, McGreal, Smyth, Cooper, & Ryley, 2000; Ahlfeldt, 2010a; Ahlfeldt & Wendland, 2010b; Osland & Thorsen, 2008). One of the key motivations for their application in the empirical literature has been the attempt to move away from the idea that all economic activity within a city is concentrated in a single dimensionless point named the central business district (CBD). In employment gravity equations, instead, properties are related to the effective distribution of employment by modeling their prices as a function of distance to all (employment) locations in a city or region, which receive distinct weights depending on the associated transport cost. Evidence for a significant and sizable effect of accessibility modeled in such a way has been provided for the Norwegian region of Rogaland (Osland & Thorsen, 2008) and the metropolitan region

of Berlin, Germany, where such employment accessibility measures could entirely explain the residential land price (to CBD) gradient (Ahlfeldt, 2010a).

While in the aforementioned cases the empirical specifications have been set up in rather an ad hoc manner, it is simple to motivate these specifications theoretically within a bid-rent framework. In a simplistic world, mobile individuals derive their utility $U(S, C, A(x))$ from the consumption of housing space (S) and a composite non-housing good (C) as well as accessibility (A), which in turn depends on location (x) relative to all other locations (y). Direct preferences on accessibility can result e.g. from non-monetary inconvenience of travelling and the desire to locate centrally within a pool of employment opportunities as well as correlated amenities. Assuming a linear city, (employment) accessibility A(x) at any local $x(y)$ is easily described (Fujita & Ogawa, 1982).

$$A(x) = \int a(y) \, e^{-bd(x,y)} dy \qquad (1)$$

where $a(y)$ is the density at location y, b is a transport cost parameter and $d(x,y)=|x-y|$ is a measure of distance between both locations. Households take the distribution of economic activity within the city as given and spend their exogenous income on the accessibility of their place of residence, which is implicitly priced at θ, housing, with an associated bid-rent of $\psi(x)$ for one unit of space and a composite consumption good whose price is the numeraire. Assuming a Cobb-Douglas type utility function for simplicity $\big(U = S^\beta C^\gamma A(x)^{1-\beta-\gamma}\big)$, maximization conditional on the budget constraint yields the following equilibrium conditions that must hold for the bid-rent at location x.

$$\psi(x) = \frac{\beta}{1-\beta-\gamma} \frac{A(x)}{S} \theta \qquad (2)$$

$$\psi(x) = \frac{\beta}{\gamma} \frac{C}{S} \qquad (3)$$

Evidently, bid-rents increase in accessibility as the first-order condition is strictly positive.

$$\frac{\partial \psi(x)}{\partial A(x)} = \frac{\beta}{1-\beta-\gamma} \frac{1}{S} \theta > 0 \qquad (4)$$

The marginal effect depends on preferences, the value of accessibility reflected in the (implicit) price θ as well as the amount of housing space consumed. As evident from equation (3) households substitute away from housing consumption as rents go up.

$$\frac{\partial S}{\partial \psi(x)} = -\frac{\beta}{\gamma} \frac{C}{\psi(x)^2} < 0 \qquad (5)$$

Equation (2), thus, further specifies the functional form of the bid-rent function. Given that bid-rents must increase in accessibility and housing consumption decreases in the price of space, housing consumption must be lower at more accessible locations. This in turn leads to a larger marginal effect of accessibility at more accessible locations and a convex accessibility gradient as in standard (monocentric) bid-rent models.

In order to capture accessibility in the spirit of equation (1) empirically, I define a gravity labor market accessibility indicator that takes the established potentiality form and links a postcode area i to a ward j.

$$EP_i = \sum_j \frac{E_j}{E} e^{-\tau TT_{ij}} \tag{6}$$

where E_j/E is the share of employment at ward j at the total employment of the Greater London Area, TT_{ij} is the transport cost incurred in terms of travel time when traveling from i to j and τ is the decay parameter determining how households discount the value of employment at location j on travel time. In practice, there are a variety of reasons for why households are supposed to value general access to employment opportunities, e.g. reduced frictions, which will be particularly important when the frequency of job changes is high and more than one person per household works. Note that if all employment is concentrated in a single location, the equation collapses to a standard monocentric framework where people commute along a shortest distance or travel time path into the dimensionless central business district. In a world of dispersed employment, areas with high employment potentiality (EP) will be those which offer good (labor market) access to many households and where, all else being equal, equilibrium rents and prices will be highest.

Throughout this paper I presume that realized property transaction prices (P) at location i are a function of the overall economic climate (Y) at time t, the structural attributes of a property (S), various location attributes (L) as well as the employment potentiality.

$$P_{it} = f(Y_t, S_{it}, L_i) + g\left(\sum_j \frac{E_j}{E} e^{-\tau TT_{ij}}\right) \tag{7}$$

Taking a strict partial equilibrium perspective I assume that for relative small alterations to the transport network f and g remain stable so that changes in property prices (ΔP) are determined by changes in the travel time between any pair of locations i and j (ΔTT_{ij}).

$$\Delta P_{it} = g\left(\sum_j \frac{E_j}{E} e^{-\tau \Delta TT_{ij}}\right) \tag{8}$$

For the purpose of this paper, my primary objective is to thus estimate $g(EP)$. The reduced form empirical specification that is taken from the data builds on a long tradition of hedonic modeling (Rosen, 1974). Property prices per square meter floor space are used as the dependent variable as they are conceptually closer to the bid-rent framework than the price of a dwelling unit. While a log-log specification has enjoyed popularity in the literature, I deliberately choose the log-linear functional form for the employment accessibility variable to satisfy the convexity requirement laid out above.

$$\log (P_{it}) = \sum_m \gamma_m S_{itm} + \sum_n \gamma_n L_{in} + \alpha_1 \sum_j \frac{E_j}{E} e^{-\alpha_2 TT_{ij}^{PRE}} + \varphi_t + \varepsilon_{it} \tag{9}$$

where S_m and L_n are vectors of structural and locational characteristics that are common in the hedonic literature, φ_t stands for a set of yearly time effects and ε is an error term satisfying the usual conditions. Other Greek letters stand for parameters to be estimated. I note that while most of the employed control variables are uncontroversial, some neighborhood controls potentially give rise to endogeneity concerns if households sort themselves with respect to accessibility depending on these socioeconomic criteria. The inclusion of a control for floor space also seems critical in light of the expected substitution between space and accessibility. On the one hand, it is likely that smaller dwelling units in the center are the results of higher densities which, in turn, are caused by higher prices and eventually better accessibility. On the other hand there could be reasons for square meter prices varying with the size of dwelling units that are not related to accessibility, which should be controlled for. In practice, parameters in equation (9) proved very stable to changes in the model specification so that I keep all variables in the benchmark specification.

It's notable that in an equation like (9), the likelihood of successfully isolating a pure labor market accessibility effect with the employment potentiality variable critically depends on whether various location amenities can be controlled for and/or whether unobserved amenities are distributed randomly with respect to employment. While I include some controls for amenities in the location controls in the empirical specification, it is quite likely in practice that the potentiality variable captures at least partially the effects of correlated amenities. For the purposes of this paper, however, this issue is not really critical as the objective of the model is to capture the benefits related to (network) accessibility and the question where they actually arise from is, in some sense, of second order.

To estimate equation (9), of course, a feasible approximation of travel times is essential. As a minimum criterion, travel times should take into account the LU/DLR network architecture, acknowledge that a train ride will eventually include initial and subsequent sections to and from stations of departure and destination and feature a choice for passengers to use an alternative transport mode. Note that I estimate equation (9) for a period covering 1995 to 1998, which is prior to the Jubilee Line and DLR extension. Travel times TT_{ij}, correspondingly refer to this period, which will be denoted *PRE* in the remainder of this article. Then, I rerun the calculations for an updated network with the respective extensions (*POST*) and predict changes in property prices based on the parameters estimated in equation (9). The decision rule for the calculation of travel times in both periods z can be stated as follows:

$$TT_{ij}^z = \begin{cases} \text{if } z = PRE; \; \min\left(\frac{D_{ijPRE}}{V^{non-train}}; \min\frac{D_{isPRE}}{V^{walk}} + \min\frac{ND_{sePRE}}{V^{train}} + \min\frac{D_{ejPRE}}{V^{walk}}\right) \\ \text{if } z = POST; \; \min\left(TT_{ijPRE}; \min\frac{D_{isPOST}}{V^{walk}} + \min\frac{ND_{sePOST}}{V^{train}} + \min\frac{D_{ejPOST}}{V^{walk}}\right) \end{cases} \quad (10)$$

In each period, passengers strictly base their transport decisions on travel time minimization. If they choose to use the combined LU/DLR network, their journey will consist of a trip to the nearest station of origin *s*, a shortest path journey along the network to the station *e* closest to the final destination and a final trip to the destination location *j*. Alternatively they can opt for a direct connection from *i* to *j*, which subsumes individual transport. In period *POST* after inauguration of the considered network extension, a switch from the alternative transport mode to LU/DLR or a change to another line within the LU/DLR network is only allowed if it goes along with a decrease in travel time compared to the previous situation.[2] The attractiveness of the competing transport modes denoted *non-train* for the alternative transport mode, *walk* for the journeys to and from stations and *train* for the network trips, are assumed to be reflected in their velocities. In the benchmark specification, these velocities are borrowed from the literature (Ahlfeldt, 2010a) and

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[2] Without this restriction, some passengers could be forced to make use of a new station if they have a new station nearest to their origin or destination and a new network trip is faster than individual transport, even though the old connection is faster than the new one. This special case, of course, only applies to a handful of postcodes.

reflect a *walk*ing speed of 4 km/h, an average car velocity of 25.6 km/h (*non-train*) and an average *train* velocity of 33 km/h.[3]

These assumptions are, of course, simplified and controversial. It is, e.g. not clear whether passengers, on average, tend to walk to stations or use buses or bikes, which would increase the non-train velocity. Also, the alternative transport mode does not only subsume auto vehicles, but presumably to some degree also other transport modes like direct bus connections, which slow down an average speed. Also, it is not clear whether, expressed in travel time, opportunity cost of a private and public transport trip are comparable. If, in monetary terms, private transport is more expensive, a relatively lower speed would be appropriate to equalize the effective opportunity cost. For now, I deliberately stick to these assumptions as the ambition of this section is to predict property price effects under ex-ante conditions. In the second part of this analysis, however, I will make use of the available information on the time dimension and run an extensive grid search to identify appropriate relative velocity parameters from the data. As it turns out, the assumptions made above are close to what the data tells us and within a reasonable range, the sensitivity of the model predictions is not overly concerning.

In the last step of this part of this analysis, I evaluate the predicted changes in prices due to the considered transport innovation with respect to the change in the distance to the nearest station (*d*), which is the treatment measure considered in GM transport innovations model.

$$\Delta \widehat{\log(P_{it})} = k\left(d_i^{POST} - dD_i^{PRE}\right) \tag{11}$$

A comparison of the model predictions to their empirical findings facilitates a first evaluation of the nature and quality of the prediction before I move on to adopt the innovations model in Section 4, introducing the predicted property price effects as a treatment variable.

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[3] In Ahlfeldt {, 2010 #538} the car velocity was determined based on a Forbes report. The average train velocity is in line with the information available in train schedules.

3.2 Results

Table 1 presents results for specification (9) type estimations. I start with a reduced model omitting transport controls but including the distance to the CBD in column (1). In column (2), distance to the nearest LU/DLR station is added, allowing for a spline at 2km as identified by GM. This model serves as a benchmark for the potentiality model (4) as defined in specification (9). Model (4) estimates the potentiality equation in log-log form for the purpose of comparison with previous studies. I note that for the reasons laid out in the theory section I prefer the log-linear specification so that I estimate a linearized version of equation (9) holding the decay parameter from column (3) constant to avoid a specification bias in the decay parameter estimate. Hedonic estimates offer little surprise, with the exception of distance to the nearest amenity, defined as museums, historically or aesthetically important buildings and religious sites. Counter to expectations the coefficient turns out to be positive and significant, most likely due to correlation with the distance to the CBD and potentiality variables. As omission of the amenity variable does not considerably affect the other coefficient estimates, however, there is not much cause for concern. In general, hedonic estimates are very stable across all specifications. I omit them from Table 1 to save space, but present them in Table A1 in the appendix for the model of primary interest (3).

From results in columns (1) and (2) a significantly negative relationship between prices and the distance to the CBD (defined as the LU station Holborn) is evident, which is in line with standard predictions for monocentric urban economies (e.g. Alonso, 1964; Mills, 1972; Muth, 1969). On average, each 1 km increase in distance is associated with a decline of about 2%. A similar effect is found for the distance to LU/DLR stations within 2km and about half the size beyond this threshold. This finding is in line with a consolidated body of evidence pointing to significant property price effects urban transport, although somewhat small in magnitude, which might be attributable to strong location controls. The results of primary interest are presented in column (3), where distance to the CBD and to the nearest station variables are replaced by the gravity variable. Both coefficients are positive and significant, which means feasible. The model outperforms the benchmark model in (2) both in terms of R-squared (R2) as well as the Akaike Information Criterion (AIC). Noteworthy, the explanatory power of the gravity variable is large. Calculating the standardized coefficients indicates that an increase by one standard deviation (SD) in the potentiality is associated with a 0.278 SD increase in prices, more than for any other struc-

tural or location variable. For comparison, the distance to CBD variable in (1) and (2) yields a standardized coefficient of about 0.17.

The estimated decay parameter (α_2) of 0.057 is roughly within the range found in previous studies where similar measures yielded parameters of about 0.1 (Ahlfeldt, 2010a) and 0.086 (Osland & Thorsen, 2008). The estimated implicit decay function is depicted in Figure 1 in comparison to previous evidence. The magnitude coefficient on the potentiality variable (α_1) indicates that for each increase in access to the overall economic mass of the city (measured in terms of employment) by one percentage point, prices go up by about 2.2%. As intended with the log-linear form, this point estimate translates into an elasticity that varies in the level of the employment potentiality and takes values of 0.25, 0.35 and 0.49 at the first, second (median) and third quartiles. To facilitate comparison of the estimated elasticity with previous studies, I re-estimate the potentiality impact in log-log form in (4). Not surprisingly, the point estimate of about 0.3 is close to the elasticity at the median of about 0.35 based on column (3) results. Again, these results are relatively close to the previous findings for Berlin and Rogaland, where an accessibility elasticity of about 0.25 was indicated. Furthermore, it falls within the range of the GDP to market access elasticity of 0.25-0.3, which Ahlfeldt & Feddersen (2010) find when investigating the regional economic effects of the German high speed rail line connecting Frankfurt and Cologne. It thus seems that there is a common theme emerging in this relatively young strand of research. The fact that accessibility has a somewhat stronger impact on prices in the Greater London Area as compared to the Berlin metropolitan area and the Rogaland region is comprehensive in light of the size of the London agglomeration. Overall, these results seem to be a reasonable starting point for a prediction exercise.

Fig. 1 Comparison of estimated decay functions
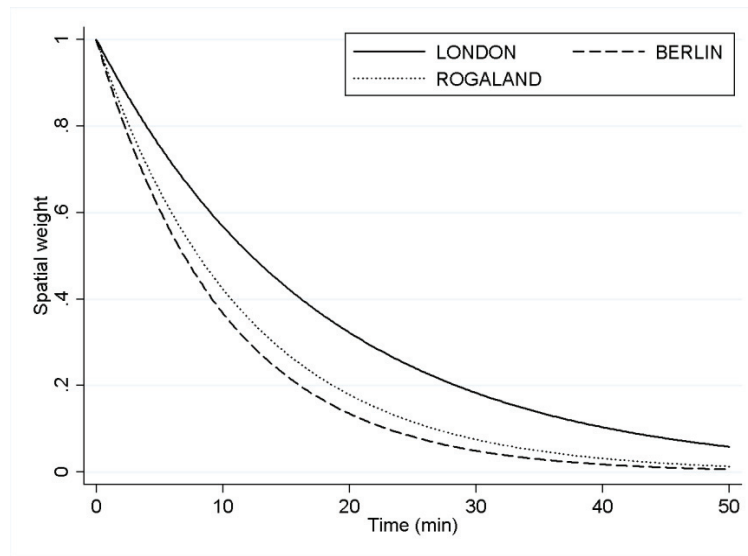
Notes: Own illustration based on own calculations and Ahlfeldt (2010a) and Osland & Thorsen (2008).

Tab. 1 Gravity model results

	(1)	(2)	(3)	(3)
	OLS	OLS	NLS	OLS
Distance to the CBD (km)	-0.020**	-0.019**		
	(0.001)	(0.001)		
Km to nearest LU/DLR | distance < 2 km		-0.020**		
		(0.003)		
Km to nearest LU/DLR | distance ≥ 2 km		-0.012**		
		(0.001)		
Employment Potentiality (α_1)			0.022**	
(in % of total employment)			(0.001)	
Decay Parameter (α_2)			0.057**	
			(0.001)	
Log of Employment Potentiality				0.308**
				(0.001)
Structural Controls	YES	YES	YES	YES
Location Controls	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Observations	60,765	60,765	60,765	60,765
R2	0.75	0.75	0.76	0.75
AIC	27584.93	27097.98	25241.03	26238.46

Notes: Dependent variable is log of purchasing price per square meter floor space in all models. Full esti-
mation results for specification (3) are presented in Table A1 in the appendix. Standard errors (in
parenthesis) are clustered on postcodes except for the decay parameter in (3). +/*/** denote sig-
nificance at the 10/5/1% level.

Based on the estimated parameters from Table 1, (3) and the transport decision rule
stated in equation (10), the model predictions for the property price effects of the 1999
Jubilee Line and DLR extension can be derived according to equation (8)
$\left(\Delta \widehat{\log(P_{lt})} = \widehat{\alpha_1} \sum_j E_j/E \, e^{-\widehat{\alpha_2}\Delta TT_{ijt}}\right)$. The resulting predicted price effects at the postcode
level are mapped jointly with the LU/DLR network in place before the extension took

place (grey) and the extended sections (red) in Figure 2. As expected, the map indicates considerable price effects around new stations. In addition, positive effects are predicted around existing stations like London Bridge or Canada Water that experienced an upgrade due to their connection to the Jubilee Line. To a more limited degree, effects further spread along the existing network to stations like New Cross (Gate), which are not directly affected by the modifications but now offer more attractive connections as a result of the opening of the Jubilee Line extension. As expected, magnitude and the spatial extent of the predicted impact vary across stations. New stations like North Greenwich that offer immediate access to the major sub-center at Canary Wharf, the downtown agglomeration (Southwark) or both (Bermondsey) are predicted to induce particularly large price effects. Stations like Lewisham, where no LU/DLR stations were present within short distances should have a wider impact than stations that are developed in areas with an already dense network (e.g. Southwark).

**Fig. 2 Predicted property price effects**
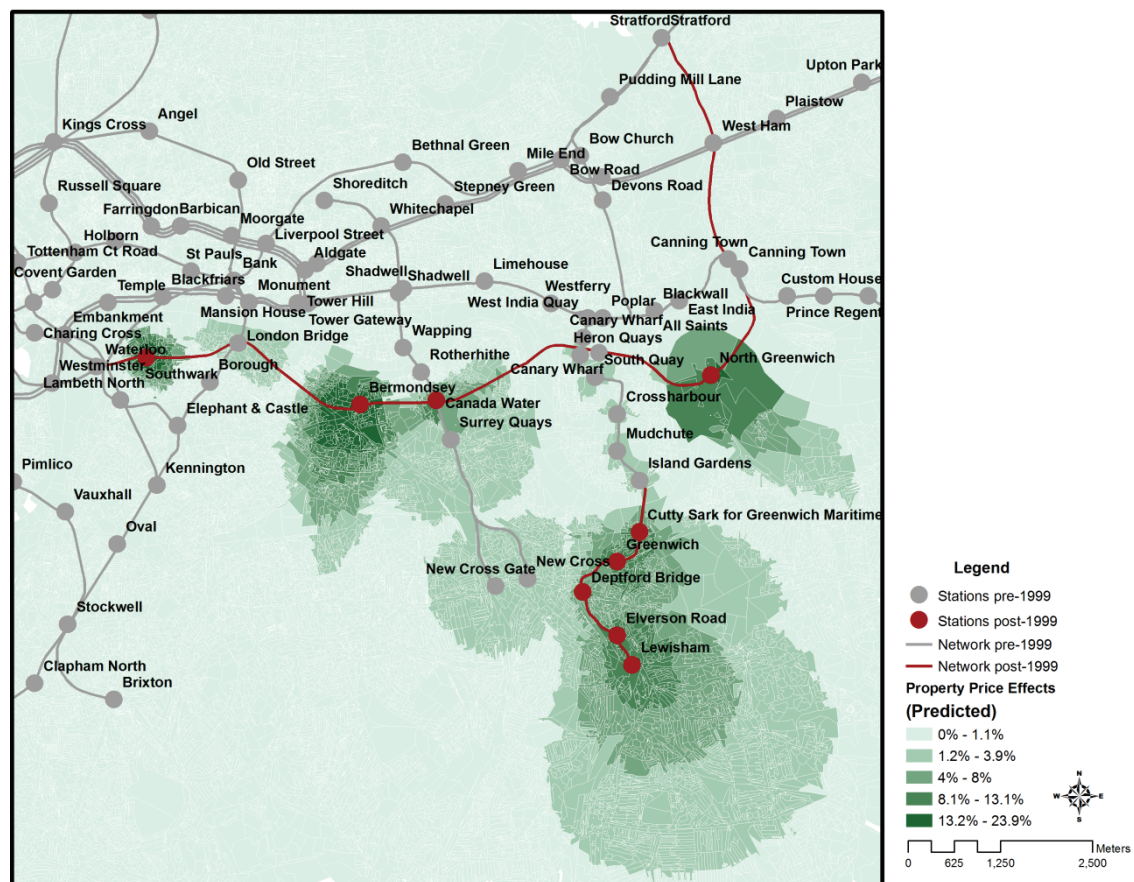
Notes: Own illustration based on own calculation.

Well reflecting the intentions of the model, the map thus indicates an accessibility treatment that is more heterogeneous than reflected by the distance to nearest station or the

respective changes. This high degree of heterogeneity becomes evident when plotting the predicted postcode effects against the experienced change in distance to nearest station. Acknowledging the spline in the station effect found by GM, I restrict the sample to postcodes that are within 2 km of a LU/DLR station post intervention. Not surprisingly, there is a negative relationship between price effects and the change in station distance. Postcodes that experience a reduction in the distance to the nearest station are generally predicted to experience larger price effects.

Marginal price effects for a given change in station distance, however, are predicted to be much higher in some areas than in others. The largest effects are actually predicted for areas that experience a relatively modest change in distance to station, which are typically postcodes along the relatively central sections of the Jubilee Line extension. In contrast, those areas that experience the largest distance treatment, which will typically be those along the southern extension of the DLR, receive relatively moderate predictions.

Fig. 3 Predicted Effects vs. Change in Distance to Station
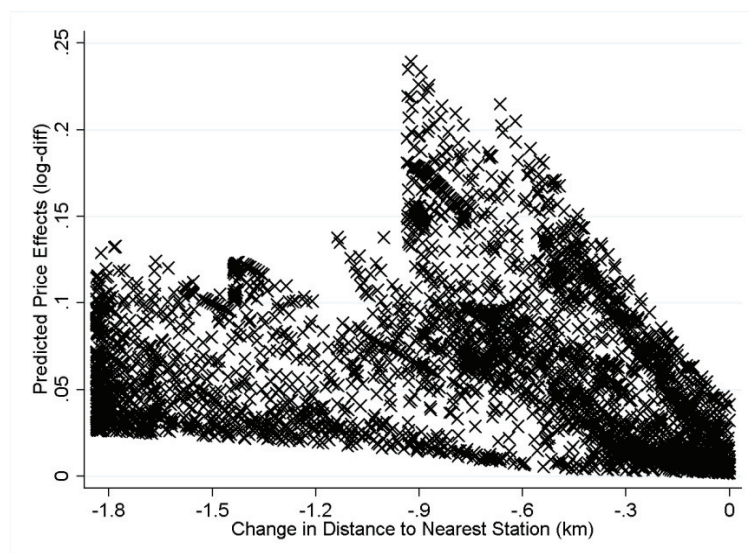
Notes: Own illustration. Sample restricted to postcodes within 2 km of a station in 2000.

Table 2 shows how the predicted effects translate into an average marginal distance to station effect that can be compared to the results from GM's transport innovations model. The table shows the results of a simple regression of predicted price effects on the change in distance to the nearest LU/DLR station, with (2 & 4) and without (1 & 3) considering the linear spline at 2 km identified by GM as well as based on the log-linear (1 & 2) and the log-log gravity specification (3 & 4). The predictions from the log-linear specifications produce marginal price effects that are within the range provided by GM, although some-

what at the upper boundary. They reproduce the spline at 2 km, after which the predicted distance to station effects are marginal. Using GM's results as a benchmark, the predictions based on the log-log gravity model clearly overestimate the price effects so that these findings support the log-linear specification that has been preferred on theoretical grounds. Furthermore, it is notable that the goodness of fit of the distance treatment variable is considerably higher when the predictions from the log-log model are used, which indicates that this model produces a considerably lower degree of heterogeneity in the station effect.

Tab. 2 Predicted Effects vs. Change in Distance to Station

	(1)	(2)	(3)	(4)
Δkm to nearest LU/DLR	-0.031**		-0.069**	
	(0.001)		(0.001)	
Δkm to nearest LU/DLR | distance ≤ 2 km		-0.053**		-0.096**
		(0.001)		(0.001)
Δkm to nearest LU/DLR | distance > 2 km		-0.004**		-0.033**
		(0)		(0)
Potentiality specification	Log-linear	Log-linear	Log-log	Log-log
Observations	30,978	30,978	30,978	30,978
R2	0.28	0.46	0.69	0.86

Notes: Depended variable is predicted change in property prices based on a log-linear (1-2) or log-log (3-4) potentiality equation. +/*/** denote significance at the 10/5/1% level.

4 Intervention Analysis

4.1 Empirical Strategy

The prediction exercise conducted in the section above has shown that the transport decision model produces a) the expected degree of heterogeneity in predicted treatment effects and b) an average treatment effect with respect to distance to the nearest station that is in line with GM's empirical results on the subject case, which are both encouraging results. In the remainder of the study I will compare the predicted effects explicitly to observed property market adjustments using a modified version of the GM transport innovations model. Adopting the same notation as in equation (9) the starting point for their model is a generalized spatial regression model.

$$\log(P_{it}) = \sum_m \gamma_m S_{itm} + \delta_1 h_{ij} d_{it} + \delta_2 (1 - h_{ij}) d_{it} + \phi_i + \varphi_t + \varepsilon_{it} \tag{12}$$

where all location features are assumed to be time-invariant and captured by a set of postcode fixed effects ϕ_i, d_{it} is the distance to the nearest LU/DLR station in period t and $h_{it} = I\{d_{it} \leq 2 \text{ km}\}$ is an indicator that distance is less or equal to 2 km. Since the network

extension changed the postcode distance relationship as new stations became nearest stations to a number of postcodes within the area, equation (12) can be estimated in a before-after analysis where time-invariant location effects are differenced out.

$$\Delta\log(P_{it}) = \sum_m \gamma_m \Delta S_{itm} + \delta_1 h_{ij}\Delta d_{it} + \delta_2 (1 - h_{ij})\Delta d_{it} + \Delta\varphi_t + \Delta\varepsilon_{it} \tag{13}$$

This transport innovations model is estimated using property data that are aggregated to postcode-unit-period level where the two considered periods are $t = PRE$ if year < 1999 and $t = POST$ if year > 1999. It provides a difference-in-difference estimate of the treatment effect as it compares prices for properties that receive a treatment (change in nearest station distance) to properties in a control group (no change) before (*PRE*) and after (*POST*) the treatment takes place. I replicate this model with yearly dummy variables and a distance to CBD × year trend interactive to capture general changes in the spatial structure of the city that are not related to the transport innovation. In addition, I estimate an extended model where, similarly, L_n × year interactive terms are included for all location controls considered in equation (9). Apart from that, the most relevant change in the baseline specification compared to GM is that I consider an extended study period ranging from 1995 to 2008 (as compared to 1997 to 2001). For further details on the model I refer to the original contribution.

This transport innovations model is easily generalized to the gravity accessibility approach used in this study. Starting from equation (9), substituting location controls (L_n) by postcode fixed effects and taking first difference yields:

$$\Delta\log(P_{it}) = \sum_m \gamma_m \Delta S_{itm} + \alpha_1 \sum_j \frac{E_j}{E} e^{-\alpha_2 \Delta TT_{ij}} + \Delta\varphi_t + \Delta\varepsilon_{it} \tag{14}$$

Again, properties that receive a treatment (increase in accessibility) are compared to a control group with properties that remain unaffected. Note that I hold employment levels constant across periods as changes in the employment distribution could be endogenous to the transport innovation. The overtime variation in the gravity variable is, thus, entirely driven by changes in the travel time matrix. In the empirical specification I also hold the parameters $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ constant at the values estimated from the cross-sectional gravity models, which is equivalent to using the predicted changes in prices as a treatment variable, given that $\Delta\widehat{\log(P_{it})} = \widehat{\alpha_1} \sum_j \frac{E_j}{E} e^{-\widehat{\alpha_2}\Delta TT_{ijt}}$.

The estimation equation thus takes the following form:

$$\Delta\log(P_{it}) = \sum_m \gamma_m \Delta S_{itm} + \Psi\left[\widehat{\alpha_1}\sum_j \frac{E_j}{E}e^{-\widehat{\alpha_2}\Delta TT_{ij}}\right] + \Delta\varphi_t + \Delta\varepsilon_{it} \tag{15}$$

The parameter of interest is Ψ, which will take the value of 1 if prices adjust one-to-one to the predictions. If the parameter is $0 < \widehat{\Psi} < 1$, prices do not fully adjust implying that the model overestimates the true impact. The opposite holds for $\widehat{\Psi} > 1$ while $\widehat{\Psi} \leq 0$ would indicate that predicted and current price effects were uncorrelated or negatively correlated, which would make the model predictions pointless.

Following a descriptive comparison of observed and predicted price effects, I estimate both versions of the transport innovations model in the next sub-section. In addition, both treatment variables are included into a single estimation specification in order to evaluate whether, conditional on the predicted effects, there are any significant average station distance effects remaining that are not captured by the model. A range of robustness checks are conducted to address concerns regarding sample selection issues and unobserved spatial heterogeneity. In the last sub-section of this chapter, I conduct a sensitivity analysis with respect to the relative transport cost assumed for different transport modes. I re-estimate equations (9) and (15) with varying transport cost parameters. The set of velocity parameters that brings $\widehat{\Psi}$ as close to 1 as possible is interpreted as the best approximation of perceived relative transport costs within the area where the extension took place. The set of R2 maximizing velocity parameters is supposed to best describe the average perceived relative transport cost within the Greater London Area, which does not necessarily need to coincide with the impact area of the network extension.

4.2 Results

Before discussing the estimation results for the transport innovations models, I present basic results from a difference-in-difference analysis of the observed and predicted treatment effects. Using the GM definition, I assign postcodes to the treatment group if they experience a reduction in nearest station distance and the outcome distance is less than 2 km $\left(d_i^{POST} - d_i^{PRE} < 0 \,\&\, d_i^{POST} \leq 2\text{km}\right)$. All other postcodes form the control group. Prices are aggregated to postcode-period-cells separately for the *PRE* and *POST* periods. Only matched pairs of postcodes with transactions in both periods are considered. Note that the postcode level is the highest spatial detail available in the dataset, thus, further disaggregation would not increase the geographic precision. As noted above, a typical postcode unit contains only about 10-15 households and represents a fairly low level of geographic aggregation.

Table 3 compares the observed and predicted changes in mean (log) prices for the treatment and control group. As a result of the larger study period the sample is substantially larger in all categories compared to the analysis by GM. First of all it is striking that the observed changes in (log) prices are quite large within both the treatment (1) as well as the control (2) group, pointing to an average growth of more than 170% over an 8.5-year period. In line with GM's findings, mean growth in the treatment group is larger than in the control group. The 4.5% effect, however, is somewhat smaller than that found by GM and a regression-based t-test, which is equivalent to a difference-in-difference (DD) estimate, fails to reject the H0 of a zero-difference (3).[4] Strikingly, the respective DD estimate based on the predicted price effects yields almost the same average treatment effect (6). Furthermore, the mean effects within the control group are very close to zero (5) indicating that, on a city-wide scale, the gravity model and the GM approach yield almost congruent control groups.

Tab. 3 Descriptive analysis of treatment effects

	Current			Predicted		
	Treatment	Control	DD	Treatment	Control	DD
	(1)	(2)	(3)	(4)	(5)	(6)
Δlog(P)	1.047	1.003	0.045	0.044	0.000	0.044**
	(0.551)	(0.573)	(0.036)	(0.032)	(0.002)	(0.002)
Sample	258	15,005	15,263	258	15,005	15,263

Notes: Selection criteria for the treatment group are postcodes that satisfy $\left(d_i^{POST} - d_i^{PRE} < 0 \text{ and } d_i^{POST} \leq 2\text{km}\right)$. log prices are aggregated to postcode-period ($PRE/POST$) cells. A definition of the DD estimate is in footnote 4. Standard errors are bootstrapped in (6). ** denotes significance at the 1% level.

Table 3 results are indicative of a proportional relationship between current and predicted price effects. They are, however, not conditioned on property characteristics, within period time effects and changes in the spatial structure of the city that are not related to the transport innovation. Furthermore, heterogeneity within the treatment group remains unconsidered. The transport innovations specifications (13) and (15), whose results I present in Table 4, offer more detailed insights. The GM specification in model (1), which allows for a spline at 2 km in the distance to nearest station effect and controls for housing and time-invariant location characteristics, time effects and a year × distance to CBD interactive term, serves as a benchmark. It reveals a station proximity effect on property prices

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[4] The difference-in-difference estimate compares the change in mean (log) prices between the periods before (PRE) and after ($POST$) the innovation and the treatment (T) and control (C) group $DD = \left(\log\left(\overline{P_T^{POST}}\right) - \log\left(\overline{P_T^{PRE}}\right)\right) - \left(\log\left(\overline{P_C^{POST}}\right) - \log\left(\overline{P_C^{PRE}}\right)\right)$.

of about 3.3% for any 1 km reduction in distance to a LU/DLR station (1). This is effect is slightly larger than revealed by comparable specifications in GM, which seems comprehensive in light of the considerably extended study period that potentially facilitates further price adjustments. This effect proves robust in the more demanding specification where adjustments in marginal prices for all observable location characteristics are allowed for (4). Confirming the previous finding of a significant spline, there are no significant station effects beyond a 2 km (outcome) distance.

Of course, the specification of primary interest in the context of this analysis is the one based on the gravity accessibility variable. Results in column (2) show that the coefficient of interest $\widehat{\varphi}$ is positive, significant and very close to 1. It is even closer to 1 in the extended specification (5). Evidently, the model overestimates the true property price effects on average, although only to a fairly limited degree. Moreover, it is notable that the gravity-based treatment variable outperforms the more conventional station distance-based counterpart in terms of R2 and AIC. This victory, however, is not too glorious in light of the small differences in the scores of the information criteria and the somewhat limited contribution in explaining the variance of the observed price changes. Standardized coefficients yield an impact in the magnitude of about 0.01 SD in the dependent variable for each 1 SD change (again, the gravity measure outperforms the distance treatment). Another way to look at the efficiency of the gravity measure is to check whether they capture all variation that is systematically related to distance to the station. This seems to be the case as the effect of station proximity is reduced to virtually zero once both treatment variables are included jointly in the model (3 & 6). This is a similar result to Ahlfeldt (2010a) where, however, a purely cross-sectional research design is employed.

It seems to be an attractive feature of the gravity accessibility variable not to overestimate station effects when being calibrated in a cross-sectional model. As shown by GM, distance to station variables are sensitive to cross-sectional bias due to correlated unobservable location characteristics, which might at least partially explain some of the relatively large estimates on station distance effects available in the literature (Debrezion et al., 2007).

Note that I run a number of robustness tests to evaluate the sensitivity of these results and detect potential sample selection problems. Selected models where I subsequently narrow down the sample are shown in Table A2 in the appendix. First, I reduce the study area to a circle within 20 km (1) and then to 15 km (2) of Bermondsey station. On the reduced sam-

ple, I run a weighted regression where I weight observations by the product of transactions in the two periods within a postcode to give higher weights to pairs of year-period cells with a large number of transactions in both periods (3). With a similar intention, I exclude all observations which have less than two observations in each of the matched year-period cells in (4). In this specification, spatial LM tests detect a significant degree of spatial dependency, favoring a lag-model over an error correction model, whose results are presented in column (5). A possible explanation for the autoregressive structure in the dependent variable might be that buyers and sellers orientate themselves at previous transactions in a neighborhood when negotiating transaction prices. By and large, the results prove to be fairly robust with a coefficient of interest ($\widehat{\Psi}$) in the region of one and statistically different from zero.

Tab. 4 Transport innovations model and predicted property effects

	(1)	(2)	(3)	(4)	(5)	(6)
Δkm to nearest LU/DLR	-0.033**		-0.005	-0.033**		-0.003
| distance < 2 km	(0.012)		(0.02)	(0.012)		(0.020)
Δkm to nearest LU/DLR	-0.015		-0.008	-0.011		-0.004
| distance ≥ 2 km	(0.013)		(0.014)	(0.013)		(0.012)
Predicted effects ($\widehat{\Psi}$)		0.951**	0.846+		0.971**	0.907*
$\Delta\widehat{\log}(P)$		(0.302)	(0.470)		(0.342)	(0.424)
Year Effects	YES	YES	YES	YES	YES	YES
Postcode Effects	YES	YES	YES	YES	YES	YES
Distance to CBD×Trend	YES	YES	YES	YES	YES	YES
Loc. Controls×Trend				YES	YES	YES
Observations	15,263	15,263	15,263	15,259	15,259	15,259
R-squared	0.79	0.79	0.79	0.79	0.79	0.79
AIC	2907.74	2902.81	2906.51	2513.66	2590.40	2513.33

Notes: Dependent variable is log of property prices per square meter floor space. Standard errors (in parentheses) are robust in (1) and (3) and bootstrapped in (2/3) and (5/6). +/*/** denote significance at the 10/5/1% level.

4.3 Sensitivity Analysis

So far, the (relative) velocities on which the transport decision model depicted in (2) builds have been defined-based assumptions that were borrowed from the literature. Given that there is a considerable degree of uncertainty regarding the appropriate choice of relative transport costs associated with different transport modes and these assumptions, thus, are quite controversial, a natural question to ask is how sensitive the results presented in the paper are with respect to the choice of the cost parameters. Therefore, I rerun the basic stages of the empirical analysis, i.e. Table 1 (3), Table 2 (1) and Table 4 (5) models for a range of feasible velocity parameters V^{walk} and $V^{non\text{-}train}$. Given that for the functionality of the model the relative cost parameters are relevant, I hold V^{train}

constant at 33 km/h, which is relatively uncontroversial based on current train schedules. I consider all 140 combinations of V^{walk}={4, 5, 6, ..., 10}km/h and $V^{nontrain}$={11, 12, 13, ..., 30}km/h. The threshold after 10km/h is chosen as this is roughly the average velocity for buses based on a random search of bus schedules. I assume buses to be the fastest mode to stations and the slowest mode for direct connections between each pair of locations. The upper boundary of the interval is constrained by the inherent logic of the model as at faster velocities no passenger would choose the LU/DLR based on travel time minimization.

As noted above, the primary objective of this quite extensive sensitivity exercise is to identify relative cost parameters from the data. Two selection criteria can be considered, a) the set of relative cost parameters that maximize the R2 in the cross-sectional regressions of type (9) and b) the set of parameters that minimizes $|\hat{\Psi} - 1|$ in the transport innovations model (15). Note that some care is required when interpreting the identified parameters. In principle, (relative) velocities reflect the opportunity cost associated with a journey of a given distance expressed in terms of time. Although in high income environments, opportunity cost of travel time may be dominating, monetary commuting costs should still matter. If monetary costs per unit of distance matter and differ between transport modes this may affect the identified velocities. If, e.g. monetary costs of individual transport are high compared to public transport, commuters will require a significant time premium to switch to private transport. Suppose that V^c is the effective average velocity of private transport in a metropolitan area and λ is the rate at which commuters are indifferent between private and public transport ($V^{public}/V^{private}$= λ) taking into account all non-time related factors like monetary cost and inconvenience, then the identified velocity for non-LU/DLR journeys would correspond to $V^{non-train}$=λ$V^{private}$. A very low $V^{non-train}$ parameter would, hence, be indicative for a conversion parameter λ that is substantially larger than one and correspondingly high non-time cost of private transport.

The results of the grid search are depicted in Figure 4 where the abovementioned selection criterion scores are plotted in a 3D space (on the z-axes) against the assumed walking (V^{walk}) and non-train ($V^{non-train}$) velocities. From the resulting R2 surface (right) it is evident that the gravity model is robust in the sense that all estimated $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ parameters are feasible (positive and significant). Moreover, a model fit is produced that exceeds the standard set by the distance-based benchmark model (Table 1, column 2) for

all (relative) cost parameters. The sensitivity surface further indicates that, in reference to the whole Greater London Area, relatively low velocities for the alternative transport mode ($V^{non\text{-}train}$) produce the highest explanatory power. The maximum is achieved at the combination of V^{walk} 7 km/h and $V^{non\text{-}train}$ = 13 km/h, which could be indicative of a high level of congestion, particularly at rush hours. Alternatively, these results indicate either a high share of buses (as opposed to faster individual transport) at the modal split or a large private/public cost conversion parameter λ. Both would be indicative of residents being willing to compromise on speed when making use of public transport, e.g. because of monetary savings.

More specific conclusions of the impact area of the network extension can be derived from the sensitivity surface for the estimated $\widehat{\Psi}$ coefficients (Figure 4, left). Evidently, all estimated coefficients are feasible, i.e. there is a positive (conditional) correlation of expected and predicted price effects ($\widehat{\Psi} > 0$). The model tends to overestimate price effects for combinations of high walking and high non-train velocities $(\widehat{\Psi} < 1)$ and underestimate price effects for combinations of low walking and low non-train velocities $(\widehat{\Psi} > 1)$. The best fit $\left(min\big[|\widehat{\Psi} - 1|\big]\right)$ is actually achieved for a combination of V^{walk} 4 km/h and $V^{non\text{-}train}$ = 26 km/h, which is very close to the assumptions imposed in the benchmark models that were taken from the literature. The diagonal isoline in the middle of the 2D projection at the bottom of the 3D graph, which interpolates the results of the grid search, indicates that other combinations of velocity parameters may satisfy the benchmark criterion $|\widehat{\Psi} - 1| = 0$. An evaluation of the predicted distance to station effects (see Figure A1 in the appendix), however, supports the benchmark assumptions as the model tends to produce relatively high average distance to station effects for low car velocities, which are not in line with the empirical findings presented in the previous section as well as GM's results.

It is reassuring that the model predictions remain relatively stable within reasonable bands of assumed velocity parameters. Only for combinations of very high or very low walk and non-train velocities does the model produce ($\widehat{\Psi}$) estimates that are far away from one. Taking an arbitrary band of ±0.25 as a benchmark criterion, $\widehat{\Psi}$ is close to one for all non-train velocities in the range of 21 km/h ≤ $V^{non\text{-}train}$ ≤30 km/h, given a walking velocity of V^{walk}=4 km/h. For V^{walk}=7 km/h, taken from the set of R2-maximizing parameters, the respective non-train band would be 16 km/h ≤ $V^{non\text{-}train}$ ≤26 km/h. The

predicted average distance to station effects are within the range of GM's findings (up to about 5% per km) as long as $V^{non\text{-}train}$ ≥22 km/h (for all considered values of V^{walk}).

The results of the sensitivity analysis pretty much confirm the appropriateness of the benchmark assumptions. Nevertheless, it is obviously important to give these parameters a careful plausibility check before applying them in a forecasting model, despite the, arguably, reassuring results of the sensitivity analysis.

Fig. 4 Grid search results
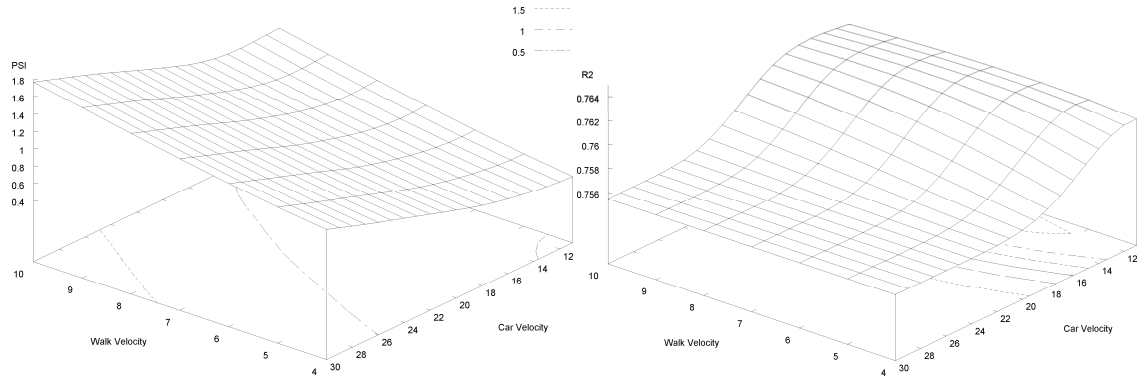
Notes: Own calculation and illustration. Figure 4a (left) presents the estimated $\hat{\Psi}$ based on equation (15). Figure 4b illustrates R2 from equation (9) type models.

5 Conclusion

This study extends a line of research that has investigated the impact of transport infrastructure improvements on property prices. The key contribution is to develop a simple empirical framework that can be used to predict property price effects of transport innovations more efficiently. Therefore, I merge a gravity-type labor market accessibility measure with a simple transport decision model in order to capture urban accessibility patterns in the presence of network-based transport systems and competing transport modes. Based on cross-sectional parameter estimates of the gravity model, property price effects of transport innovations can be predicted from scheduled changes in transport cost – here incurred in the form of travel time – between each pair of locations in the city.

This approach is shown to have several advantages over a more conventional accessibility modeling. The model accounts for the network dimension of rail-based transport systems by addressing heterogeneity of stations with respect to their place in the network hierarchy and their centrality in an urban setting. It also allows for modal switching following an improvement in a particular transport mode. Even when based on simplified assump-

tions regarding the relative costs of distinct transport modes the gravity model outperforms conventional spatial regression models in terms of explanatory power. Moreover, this approach proves less sensitive to cross-sectional bias resulting from unobserved effects that are correlated with the distance to a transport infrastructure. When comparing the findings from the cross-sectional gravity estimates to the few existing comparable studies, some general findings emerge. A 1% increase in accessibility as expressed in the travel time discounted access to employment opportunities (and correlated effects) induces a roughly 0.25-0.3 increase in property prices, although it has to be noted that there are still very few comparable studies available and previous studies have not accounted for the substitution effect in housing consumption that arises from increases in accessibility and rents.

Using the 1999 Jubilee Line and DLR extension in London as a case in point, this relatively simple and straightforward partial equilibrium approach is shown to have satisfactory predictive power. In the subject case, effective property transaction prices adjust almost one-to-one to the model predictions. At the same time, there is no systematic price variation with respect to distance to station detectable that is not captured by the model. The predicted treatment outperforms the powerful transport innovations model employed by GM, which empirically confirms the added value of a more sophisticated accessibility treatment that features station heterogeneity. A sensitivity analysis reveals that the model implications are not too sensitive with regard to the definition of relative costs for distinct transport modes within a reasonable range. Also, standard assumptions taken from the literature are confirmed when using a grid search to calibrate the model to observable price changes and back out the relative transport cost parameters.

Altogether, these results indicate that gravity accessibility variables, when incorporating transport infrastructure and competing transport modes, represent a powerful tool to model accessibility. By addressing treatment heterogeneity and being less prone to problems arising from correlations with unobserved location characteristics, they qualify as a starting point for assessment of expected property price effects during the preliminary stages of transport planning. Given the explanatory power on the one hand, and the relatively simple implementation on the other, the strategy presented in this study may be considered as an ingredient in (social) cost-benefit analyses when the potential for compensations by benefiting landlords or property tax revenues needs to be evaluated. Taking

the mean property price within the treatment area and the output area level housing stock as recorded in the 2001 census as a basis, the estimated marginal price effects from the benchmark models translate into an aggregated effect of the LU/DLR extension of almost £675 million in 1999 prices.

Finally I note that, taking the availability of appropriate data as given, the applicability of the model is neither limited to residential property nor to rail transport. Also, an extended set of assumptions would allow the incorporation of monetary and other costs into the cost matrices. With some modifications, the presented approach could be extended to any transport innovation that affects any kind of bilateral transport cost between urban locations as well as commercial property prices and the underlying agglomeration economies, although further sensitivity checks seem to be required.

Fig. A1 Grid search - predicted station proximity effects
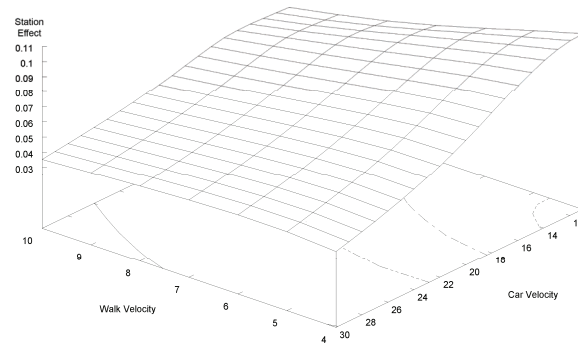
Notes: Own calculation and illustration. Estimates correspond to Table 4, (2) type models. For better visibility the magnitude of coefficients (omitting) negative signs are shown.

Tab. A1 Hedonic estimates

	(1)		(2)	
	Coeff.	S.E.	Coeff.	S.E.
Number of bedrooms	0.009**	0.002	0.018**	0.004
Number of bathrooms	0.141**	0.004	-0.009	0.007
Floor size (m^2)	-0.002**	0	-0.002**	0
Age (years)	0.001**	0	0.000**	0
Age squared	-0.000**	0	-0.000**	0
Full central heating	0.092**	0.004	0.071**	0.007
Partial central heating	0.033**	0.007	0.050**	0.011
Garage	0.080**	0.003	0.033**	0.006
Parking space	0.057**	0.004	0.013*	0.006
Detached property	0.232**	0.009	0.116**	0.018
Semi-detached property	0.007	0.006	-0.006	0.012
Terraced property	-0.074**	0.006	-0.022+	0.012
Cottage or bungalow	0.158**	0.013	0.106**	0.023
Property is new	0.200**	0.007	0.151**	0.015
Property sells under leasehold	-0.117**	0.006	-0.091**	0.013
Gravity Accessibility Variable	YES		YES	
Time Effects	YES		YES	
Postcode Effects			YES	
Location Controls	YES			
Location Controls x Trend			YES	
Period	1995-1999		1995-1999/2000-2008	
Observations	60,765		15,259	
R-squared	0.76		0.79	

Notes: Depended variable is log of price per square meter in all models. Models correspond to Table 1 (3) and Table 4(5). Standard errors (S.E.) are clustered on postcodes in (1) and bootstrapped in (2). +/*/*** denote significance at the 10/5/1% level.

Tab. A2 Robustness checks

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	WLS	OLS	SAR
Predicted effect $(\widehat{\Psi})$	1.283**	1.081**	1.262**	1.186+	0.995+
$\Delta\widehat{\log}(P)$	(0.329)	(0.323)	(0.277)	(0.703)	(0.54)
Year Effects	YES	YES	YES	YES	YES
Postcode Effects	YES	YES	YES	YES	YES
Distance to CBD×Trend	YES	YES	YES	YES	YES
Loc. Controls×Trend	YES	YES	YES	YES	YES
Study Area (km from Bermondsey)	20	15	15	15	15
Min transaction (cell)	1	1	1	2	2
Spatial correction	-	-	-	-	lag
Observations	12,692	8,644	8,544	1,696	1,696
R-squared	0.78	0.76	0.76	0.76	-
AIC	2365.0	1774.28	-288.910	-498.30	-566.35

Notes: Dependent variable is change in log of property prices per square meter floor space. Standard errors (in parentheses) are bootstrapped in (1), (2) and (4). Spatial LM test statistics from model (4) are: LM_{error}: 89.33, robust LM_{error}: 14.44, LM_{lag}: 122.20, 47.31. Model (5) uses a row standardized inverse distance weights matrix where values on the diagonal are set to zero. +/*/** denote significance at the 10/5/1% level.

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