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Article (Accepted version) (Refereed)

Original citation:
Ahlfeldt, Gabriel M. (2013) *If we build it, will they pay? Predicting property price effects of transport innovations.* Environment and Planning A, 45 (8). pp. 1977-1994. ISSN 0308-518X
DOI: 10.1068/a45429

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If we build it, will they pay? Predicting property price effects of transport innovations[*]

Abstract: In this study I apply a gravity-type labor market accessibility model to the Greater London Area to investigate house price capitalization effects. The spatial scope of labor market effects is found to be about 60 minutes. Doubling accessibility increases the utility of an average household by about 12%. I combine the gravity approach with a transport decision model that takes into account the urban rail network architecture, allows for mode switching and thus accounts for the effective accessibility offered by a station, to predict the 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 effective capitalization effects, suggesting that the approach might be a viable ingredient in transport planning.

Keywords: *Property prices, hedonic analysis, transport innovations, gravity equation*
Version: *October 2012*
JEL: H43, R40, R58

Forthcoming in Environment and Planning A

1 Introduction

Transport infrastructure projects are among the largest public expenditure programs worldwide. Among the most expensive transport projects are downtown sections of heavy rail systems as they have to be developed in densely developed cities where the opportunity cost of land is high, if not entirely underground. Crossrail, a major new high-capacity rail line crossing the Greater London Area in the East-West direction along a 22km tunnel section, is currently estimated to cost a total of about £15 billion. These huge

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* I thank seminar and conference participants at Lancaster University, TU-Dresden and the ERSA conference in Barcelona and especially Nathaniel Baum-Snow, Paul Cheshire, Steve Gibbons, Georg Hirte, Liv Osland, Rob Simmons and Bernhard Wieland for helpful comments and suggestions. Felix Weinhardt provided valuable support with the KS2 data. I also thank Eric Sheppard (the editor) and three anonymous referees for helpful comments and suggestions.

costs are counterbalanced by potential public and private benefits, which are typically assessed in social-cost-benefit analyses. Recent evidence has demonstrated the role of transport infrastructure as a major determinant of economic growth pattern (e.g. Baum-Snow, 2007; Duranton & Turner, 2011). Still, the question of how to finance and recover huge public expenditures remains open in practice. Compensations from property owners who receive an external benefit from publicly funded transport projects are one potential source of revenue. Furthermore, increases in property values naturally induce property tax revenues. Thus there is a substantial public interest in an *ex-ante* assessment of the property price effects of transport improvements, which could be considered in viability studies.

By and large, it is well-documented that property prices are higher near to transport infrastructures, in particular near urban rail systems (e.g. Ahlfeldt & Wendland, 2011; Bajic, 1983; Baum-Snow & Kahn, 2000; Bowes & Ihlanfeldt, 2001; Damm, Lerner-Lam, & Young, 1980; Dewees, 1976; McDonald & Osuji, 1995; Voith, 1993). Debrezion, Pels, and Rietveld (2007) and Bartholomew and Ewing (2011) provide useful summaries on this strand of research. The recent literature has also investigated the property price effects of transport innovations, i.e., newly developed pieces of infrastructure, which makes it easier to identify the unbiased accessibility effects (e.g. Ahlfeldt, 2011b; Ahlfeldt & Wendland, 2009; Gibbons & Machin, 2005; McMillen & McDonald, 2004).

Yet, it remains difficult to forecast the property price effects for scheduled transport innovations. The existing literature mainly provides case-based evidence on average treatment effects, e.g., how prices change at different distances to the nearest rail station. Some studies allow for heterogeneity in the station effect with respect to neighborhood characteristics or trends, with mixed results (e.g. Atkinson-Palombo, 2010; Chatman, Tulach, & Kim, 2011; Gatzlaff & Smith, 1993; Hess & Almeida, 2007). Bowes and Ihlanfeldt (2001), in addition, also control for heterogeneity with respect to distance to the central business district. The position of the station in a network hierarchy and the effective accessibility offered, however, is typically not modeled explicitly. Also, the role of alternative transport modes and effects that spread along preexisting parts of the network when new sections are added to a network are typically not considered in the transport capitalization literature. 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 the property price effects of transport innovations. In doing so, my ambition is to keep the approach as simple as possible to facilitate straightforward applications in planning.

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 all locations in a region to each other so that the role of labor market accessibility can be evaluated within an environment of dispersed employment (e.g. Ahlfeldt, 2011a; Osland & Thorsen, 2008). Second, I develop a simple transport decision model that allows modeling the transport costs incurred in the form of travel time between any pair of locations in the presence of competing transport modes. Changes in the urban travel cost matrix can then 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 an intervention analysis following the distinct approaches used by Ahlfeldt (2011b) and Gibbons & Machin (2005) (henceforth GM) to evaluate the predictive power of the gravity accessibility model.

I chose the 1999 extension of the London Underground (LU) Jubilee Line and Docklands Light Railway (DLR) network as a natural experiment mainly for 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 extension into residential areas that were not previously accessible by the LU or DLR. Thus, I expect considerable heterogeneity in terms of 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.

The empirical analyses in this paper can be categorized into two major stages. First, I apply the gravity model to the Greater London Area. This stage comes with a number of important contributions to the literature. I evaluate the functional form of the gravity equation using parametric and semi-parametric estimation techniques, identify the spatial scope of labor market effects from bilateral changes in transport costs and analyze the temporal adjustment path. With the help of the simple bid-rent model, I derive the elasticity of indirect utility with respect to accessibility and show how it varies in some population characteristics from reduced form regressions. Secondly, I conduct an out-of-sample prediction of the property price effects based on simulated changes in bilateral transport costs and cross-sectional estimates using data that was available prior to the intervention (1999). Using quasi-experimental research techniques, I compare the predictions to actual changes in property prices following the opening of the new line. Previewing my results, the paper concludes that the implemented gravity approach does well in capturing accessibility effects in the cross-section as well as forecasting the effects of changes in accessibility.

2 Framework

To guide the empirical analysis, I assume a simplistic world where perfectly mobile households of type *n* derive a Cobb-Douglas-type utility from the consumption of living space *S* and a composite non-housing good *C.* The city consists of discrete city blocks indexed by *i*.

$$U_{ni} = A_{ni}{C_{ni}}^{\alpha}{S_{ni}}^{1-\alpha} \tag{1}$$

A_i captures the effects of accessibility, which is assumed to shift utility at a given location. The accessibility level a_i could in principle be defined as the distance to the central business district as in classic urban models following the Alonso (1964) tradition. More recently, a tradition of using gravity variables to empirically describe accessibility patterns has emerged in the urban and housing literature (e.g. Adair, McGreal, Smyth, Cooper, & Ryley, 2000; Ahlfeldt, 2011a; Ahlfeldt & Wendland, 2012; Cervero, 2001; Cervero, Rood, & Appleyard, 1999; McArthur, Osland, & Thorsen, in press; Osland & Thorsen, 2008; Wang & Minor, 2002). 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 the distance to all (employment) locations in a city or region, which receive distinct weights depending on the associated transport costs. Evidence for a significant and sizable effect of accessibility modeled in such a way has been provided, for example, for the Norwegian region of Rogaland, where the gravity variable was used to disentangle the labor market effects from a broader urban attraction effect (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, 2011a). Following this literature, I use a gravity formulation of accessibility that relates each location in the city i to employment E_j at all other locations j in the city. All blocks are connected by a transport cost measure d_{ij}, which determines the spatial weight. Parameter γ_n>0 determines the overall utility effect of accessibility on utility. If employment is concentrated in one city block, the equation collapses to a standard monocentric model $\left(a_i = g(d_i^{CBD})\right)$.

$$A_{ni} = a_i{}^{\gamma_n},\ a_i = \sum_j \frac{E_j}{\sum_j E_j} g(d_{ij}) \tag{2}$$

Note that in equation (1) I have assumed share parameters that are constant across all individuals in the city. This is in line with Davis and Ortalo-Magné (2011) who show that housing expenditure shares are remarkably constant across geographies and population groups. There is, however, less reason to expect that accessibility is valued similarly by different types of households. Similar to urban agglomeration models (e.g. Ahlfeldt & Wendland, 2012; Fujita & Ogawa, 1982; Lucas & Rossi-Hansberg, 2002) I use a black-box approach to accessibility. The black-box accessibility index captures, for example, the inconvenience of travelling and the desire to locate centrally within a pool of employment opportunities. To simplify matters, I assume that in monetary terms, within-city transport costs do not vary depending on the place of residence. This assumption does not imply that monetary transport costs are irrelevant, they may still represent a substantial share of the budget. But the location-varying component is assumed to be small relative to a fixed cost, e.g., of owning a car, or using public transport, where an increase in distance traveled in practice only leads to a marginal (if at all) increase in monetary transport costs. Minimally, the implication is that the marginal increase in monetary cost in distance traveled is small relative to the inconvenience of longer journeys, which seems to be a reasonable approximation for many major metropolitan areas, including London. In any case, it is likely that the benefits of accessibility are perceived heterogeneously by individuals. I consider heterogeneous preferences to the extent that I allow γ_n to be city block-specific and a function of observable attributes of the resident population at i. Individuals are otherwise assumed to be identical.

Households take the distribution of economic activity within the city as given and spend their exogenous budget (net of monetary transport costs) B on living space, with an associated price or bid-rent of ψ_{ni} for one unit of space S and the composite consumption good whose price is the numeraire. First-order conditions imply the following indirect demand functions:

$$C_{ni} = \alpha B \tag{3a}$$

$$S_{ni} = (1-\alpha)\frac{B}{\psi_{ni}} \tag{3b}$$

To keep an individual indifferent across different locations, a household´s willingness to pay for space – the bid-rent – must adjust to maintain a reservation level $\overline{U_n}$.

$$U_{ni} = \overline{U_n} = A_{in}(\alpha B)^{\alpha}\left((1-\alpha)\frac{B}{\psi_{ni}}\right)^{(1-\alpha)} \tag{4}$$

Setting $\overline{U}_n$ to 1 for simplicity, solving for Ψ_{ni} and taking logs yields the household bid-rent as a function of accessibility.

$$\log(\psi_{ni}) = \log\left[(1-\alpha)\alpha^{\frac{1}{1-\alpha}}(B)^{\frac{1}{1-\alpha}}\right] + \frac{\gamma_n}{1-\alpha}\log(\mathrm{a_i}) \tag{5}$$

Under the assumptions and parameter restrictions ($0<\alpha<1, \gamma_n>0$) made, the bid-rents must log linearly increase in accessibility, i.e., $\partial\log(\psi_{ni})/\partial\log(\mathrm{a_i}) > 0$ and $\partial^2\log(\psi_{ni})/\partial\log(a_i)^2 = 0$. While equation (5) can be used to motivate a reduced-form estimation equation, it is important to consider that in reality instead of a household's bid-rent at various locations, a rent or price gradient is observed, which forms the envelope of all individual bid-rent curves (ψ_{ni}). In competitive markets, the price per unit of space R_i reflects the highest bid-rent at a given location $R_i = max(\psi_{i1}, \psi_{i2}, \dots \psi_{iN})$. In the equilibrium residents must choose a location *i* where the rent gradient (marginal price of accessibility) corresponds to their own valuation of accessibility, since they will otherwise be outbid by other household types or the benefits from higher accessibility will be more than compensated for by a reduction in the consumption of housing space, i.e., $\partial\log(R_i)/\partial\log(a_i) = \frac{\gamma_{in}}{1-\alpha}$.

This in turn implies that residents with a higher valuation of accessibility will sort themselves into respective high-accessibility areas. There are two important implications for the empirical analysis. First, given that $\partial\gamma_{in}/\partial a_i > 0$, the rent accessibility gradient will take a convex form, i.e., $\partial^2\log(R_i)/\partial\log(\mathrm{a_i})^2 > 0$. Second, it is possible to recover household (block) specific accessibility preferences (γ_{in}) from the local slope of the accessibility gradient at locations with a given level of accessibility a_i. The household-type-specific accessibility elasticity parameter γ_{in} can be computed as $\gamma_{in} = (1-\alpha)\,\partial\log(R_i)/\partial\log(\mathrm{a_i})$, where (1-$\alpha$) can be assumed to take a value of 0.25 as found by Davis and Ortalo-Magné (2011). This value is close to anecdotal evidence for the London housing market (NHPAU, 2007).

3 Strategy

The empirical stages of this paper are split into two major parts. First, I estimate a gravity equation model using data from the Greater London Area. In that section I pay considerable attention to identifying the appropriate functional form of the level and spatial decay parameters, which I estimate both out of a cross-section as well as using variation that stems from a change in transport infrastructure. Informed by an empirical evaluation of the gravity concept I proceed to what I consider to be the main contribution of this study; an out-of-sample prediction of property price adjustments to new transport infrastructures. A key feature of this section is the comparison of predicted and observable price adjustments. I consider this exercise important since a good fit between predicted and observable price adjustments a) lends some trust to the ability of gravity models to describe the functional relationship between (labor) market accessibility and willingness-to-pay for housing space and b) opens interesting avenues for the application of similar models in transport planning.

3.1 Estimation

Throughout this paper I presume that realized property transaction prices (P) at location i are a function of observable structural and locational attributes (X_m), yearly time effects φ_t, an observable location-specific time-invariant component (ϕ_i) and a gravity accessibility term that takes the form of an employment potentiality $\left(\sum_j \left(E_j/\sum_j E_j\right) g(TT_{ij})\right)$. In this potentiality, each location j in the city is weighted by its share at total employment and the travel time between locations i and j (TT_{ij}) where closer locations receive higher weights. This approach is in line with a large body of capitalization literature in the tradition of Rosen (1974) and assumes that after controlling for property features in hedonic regressions, observable prices (P) can be interpreted as bid-rents for homogeneous housing units as discussed in the section above. Parameters β_m are the hedonic implicit prices and ϑ a random error term.

$$\log(P_{it}) = \sum_m \beta_m X_{im} + f\left(\log\left(\sum_j \frac{E_j}{\sum_j E_j} g(TT_{ij})\right)\right) + \phi_i + \varphi_t + \vartheta_{it} \quad (6)$$

As discussed above, equation (5) cannot be viewed as a reduced form of (5) since the price gradient is the envelope of the individual willingness-to-pay of all agents in the study area. Theoretically, I expect prices to be a convex function of accessibility. A conventional way of dealing with such convexity requirements is to employ the semi-log form, which has typically proven to be a feasible approximation of distance to CBD gradients (e.g. Abelson, 1997; Ahlfeldt & Wendland, 2011; Atack & Margo, 1998), although more complex forms tend to improve the data fit (McMillen, 1996; Osland & Thorsen, 2008). Similarly, an exponential iceberg-type cost function in the gravity term $\left(g(TT_{ij}) = e^{-\tau TT_{ij}}\right)$ has enjoyed popularity in the theoretical and empirical literature (e.g. Ahlfeldt, 2011a; Ahlfeldt, Redding, Sturm, & Wolf, 2012; Ahlfeldt & Wendland, 2012; Fujita & Ogawa, 1982; Lucas & Rossi-Hansberg, 2002), but the functional form has usually been imposed a priori.

While I adopt these popular functional forms in my benchmark specifications, I evaluate the plausibility of the approximations using semi-parametric parametric techniques that do not impose an a priori functional form on $f(.)$ and $g(.)$. I estimate the gravity equation (6) using cross-sectional variation in transport costs and – to my knowledge for the first time in the gravity capitalization literature – using spatiotemporal variation that stems from changes in bilateral travel times due to a transport innovation.

Spatial models

The starting point of the analysis is a semi-log gravity equation with exponential cost function estimated from cross-sectional variation in bilateral travel times between postal codes *i* and 649 wards *j* in the Greater London Area. Wards are a useful spatial unit to base the gravity variable on since their definition follows the economic geography, i.e., wards are typically very small and provide a high spatial detail where employment densities are high. In the cross-sectional estimates I restrict the sample to observations prior to the Jubilee and DLR extension discussed above. Unobserved location characteristics (ϕ_i) enter the error term ε. The parameters of interest are α_1, which reflects the marginal benefit of increases in accessibility as perceived by the local population in *i*, and α_2, which describes the rate at which surrounding employment is discounted as travel times increase. A positive labor market accessibility effect requires both parameters to be positive. To simultaneously identify both parameters, equation 7a) is estimated using a non-linear least squares method (NLS).

$$\log(P_{it}) = \sum_m \beta_m X_{im} + \alpha_1 \left(\sum_j \frac{E_j}{\sum_j E_j} e^{-\alpha_2 TT_{ij}} \right) + \varphi_t + \varepsilon_{ij} \quad (7a)$$

To allow for a flexible functional form in the spatial discount with which remote locations *j* enter the employment potentiality, I create a series of "employment bins" (EB) b. These bins capture the share of local employment that is accessible within a given time interval from location *i:* $EB_{ib}^{vw} = \sum_j E_j / E \; \forall \; v < TT_{ij}^{PRE} \leq w$, where v and w form the boundaries of a "bin" covering a five-minute interval (e.g., 0-5, 5-10,…,55–60min). To each of these bins *b* I ascribe a travel time that corresponds to the center of the respective interval (e.g., 2.5, 7.5,…,57.5min). Jointly, parameters α_b form a non-linear index describing the impact of employment accessibility at different travel times.

$$\log(P_{it}) = \sum_m \beta_m X_{im} + \sum_b \alpha_b EB_{ib} + \varphi_t + \varepsilon_{ij} \quad (7b)$$

In order to evaluate whether the semi-log specification is an appropriate approximation of the expected convexity of the gradient, I run a semi-parametric version of model (7a), where, holding the decay parameter ($\widehat{\alpha_2}$) constant, I estimate the non-linear relationship between (log) prices and employment potentiality *f*(.) using locally weighted regressions while assuming (semi-log) linear effects for all control variables. This partially linear model is estimated using the first differencing technique as implemented by Lokshin (2006).

$$\log(P_{it}) = \sum_m \beta_m X_{im} + f\left(\log\left(\sum_j \frac{E_j}{\sum_j E_j} e^{-\widehat{\alpha_2} TT_{ij}} \right) \right) + \varphi_t + \varepsilon_{ij} \quad (7c)$$

As discussed, individual bid-rents must be tangent to the land price gradient at all locations. From the local slope of the (non-linear) accessibility gradient f'(.) at a given level of accessibility (employment potentiality), the elasticity of indirect utility with respect to accessibility can be computed for the local population in *i*: $\gamma_i = (1-\alpha) f'(.)$. These local elasticity estimates and the implicit utility effects can then be associated with some population characteristics (Z_n) in second stage regressions.

$$\widehat{\gamma_i} = \delta_0 + \sum_n \delta_n Z_{in} + \mu_i \quad (8)$$

Spatiotemporal models

A key challenge in the estimation of transport infrastructure effects is the separation from correlated unobserved effects, e.g., useful public and private services that co-locate with train stations. This is a special case within the broader problem in social sciences of separating treatment effects from correlated individual effects. Quasi-experimental research designs, where an individual's response to a treatment is analyzed over time, allow for unobserved time-invariant individual effects. I employ two variations of difference-in-difference (DD) designs where the first difference is taken over space (different degrees of accessibility treatment) and the second difference is taken over time (before vs. after).

Firstly, I estimate a long-difference version of equation (7a). Similar to GM I take long differences in property prices over the periods before and after 1999 ($\Delta\log(P_{ic})$). Therefore, observations in both periods are aggregated to the postcode level, a spatial unit that usually encompasses about 10–15 households. This approach essentially corresponds to a repeated sales estimator at the postcode level. Instead of using the change in distance to the nearest station as a treatment as in GM, I consider changes in bilateral transport cost as accessibility treatment $\left(\Delta\left(e^{-\alpha_2 TT_{ij}}\right) = e^{-\alpha_2 TT_{ij}^{POST}} - e^{-\alpha_2 TT_{ij}^{PRE}}\right)$. Since the employment location is potentially endogenous, I fix the distribution of employment to 2001 in both periods to ensure that the accessibility effect is identified from variations in travel time alone. Similar to 7a), equation 9a) is estimated using NLS. As in the spatial models, I estimate an employment "bin" specification to allow for a more flexible functional form of the spatial decay (9b). An attractive feature of both variations of the repeated sales model is that unobserved time-invariant location features (ϕ_i) are differentiated out.

$$\Delta\log(P_{ic}) = \sum_m \beta_m X_{im} + \alpha_1 \sum_j \frac{E_j}{\sum_j E_j} \Delta\left(e^{-\alpha_2 TT_{ij}}\right) + \Delta\varphi_t + \Delta\varepsilon_{it} \quad (9a)$$

$$\Delta\log(P_{ic}) = \sum_m \beta_m X_{im} + \sum_b \alpha_{\mathrm{b}} \Delta EB_{ib} + \Delta\varphi_t + \Delta\varepsilon_{it} \quad (9b)$$

Secondly, I estimate a quasi-panel model similar to Ahlfeldt (2011b), which allows for time-varying treatment effects by interacting the treatment measure $\left(Y_i = \sum_j \left(E_j / \sum_j E_j\right) e^{-\widehat{\alpha_2} TT_{ij}}\right)$ with a full set of yearly time effects φ_t. Choosing 1999 as a base year, I obtain a set of treatment coefficients α_{1t} that form an index of temporal adjustment, which allows for anticipation effects or gradual adjustments in prices due to costly spatial arbitrage. In this setup, standard panel regression techniques can be used to control for unobserved time-invariant local features (ϕ_r) via fixed effects. Due to the relatively large number of treatment effects (13), I increase the cell size of the fixed effects to wards in this specification.

$$\log(P_{it}) = \sum_m \beta_m X_{im} + \Xi Y_i + \sum_{t \neq 1999} \alpha_{1t}(Y_i \times \varphi_t) + \phi_r + \varphi_t + \varepsilon_{it} \tag{10}$$

3.2 Prediction and evaluation

Taking a partial equilibrium perspective and assuming that for relative small alterations to the transport network $f(.)$ and $g(.)$ remain stable, changes in property prices ($\Delta\log(P)$) can be predicted by changes in the travel time between any pair of locations i and j (TT_{ij}) and the parameter estimates from the spatial models discussed above.

$$\Delta\widehat{\log(P_{it})} = \widehat{\alpha_1}\left(\sum_j \frac{E_j}{\sum_j E_j}\left(e^{-\widehat{\alpha_2}TT_{ij}^{POST}} - e^{-\widehat{\alpha_2}TT_{ij}^{PRE}}\right)\right) \tag{11}$$

There are, in principle, at least two ways of evaluating the quality of the predictions made. Firstly, the predicted treatment effect can be compared to the independent estimates by GM. Adopting the same specification as in GM, the predicted changes in property prices should be a spline function $k(.)$ of the changes in distance to the nearest station.

$$\Delta\,\widehat{\log(P_{it})} = k(h_i \Delta d_i + (1 - h_i)\Delta d_i) \tag{12}$$

, where $\Delta d_i = \left(d_i^{POST} - d_i^{PRE}\right)$ and $h_i = I(d_{it} \leq 2\text{ km})$ is an indicator that the outcome distance is less or equal to 2km.

Secondly, the predicted property price changes can be directly benchmarked against observable property price changes. The spatiotemporal models (9 and 10) provide a useful starting point for a test. To evaluate the relationship between predicted and observable property prices I use the former $\Delta\widehat{\log(P_{ic})} = \left[\widehat{\alpha_1} \sum_j E_j / \sum_j E_j \, \Delta\left(e^{-\widehat{\alpha_2}TT_{ij}}\right)\right]$ as a treatment variable in the repeated sales and quasi-panel model, which I collapse to a simple two-period (before/after) model. Evidently, the parameter of interest Ψ 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 are uncorrelated or negatively correlated.

$$\Delta\log(P_{ic}) = \sum_m \beta_m X_{im} + \Psi\left[\widehat{\alpha_1} \sum_j \frac{E_j}{\sum_j E_j} \Delta\left(e^{-\widehat{\alpha_2}TT_{ij}}\right)\right] + \Delta\varphi_t + \Delta\varepsilon_{it} \tag{13}$$

$$\log(P_{it}) = \sum_m \beta_m X_{im} + \Xi\left[\widehat{\alpha_1}\sum_j \frac{E_j}{\sum_j E_j}\Delta\left(e^{-\widehat{\alpha_2}TT_{ij}}\right)\right]$$
$$+\Psi\left[\widehat{\alpha_1}\sum_j \frac{E_j}{\sum_j E_j}\Delta\left(e^{-\widehat{\alpha_2}TT_{ij}}\right)\right] \times POST_t + \phi_i + \varphi_t + \varepsilon_{it} \quad (14)$$

4 Data

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 study period considered in this analysis ranges from January 1995 to July 2008 (as opposed to 1997–2002 in GM). A postcode reference facilitates merging individual transactions with other data in a GIS environment. Such important sources include the national pupil database and the 2001 census. A detailed description of the data, including the spatial variables used as *location controls* is in the appendix.

To estimate equation (9) 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 will feature a choice for passengers to use an alternative transport mode. I compute two sets of travel times. The first set that is for a period covering 1995 to 1998, which is prior to the Jubilee Line and DLR extension, will be denoted *PRE* in the remainder of this article. Then, I rerun the calculations for an updated network with the respective extensions (*POST*). The decision rule for the calculation of travel times in both periods z can be stated as follows:

$$TT_{ij}^{z} = \begin{cases} \text{if } z = PRE;\ \min\left(\frac{D_{ijPRE}}{V^{non-train}}; \min\frac{D_{isPRE}}{V^{walk}} + \min\frac{ND_{sePRE}}{V^{train}} + \min\frac{D_{ejPRE}}{V^{walk}}\right) \\ \text{if } z = POST;\ \min\left(TT_{ijPRE}; \min\frac{D_{isPOST}}{V^{walk}} + \min\frac{ND_{sePOST}}{V^{train}} + \min\frac{D_{ejPOST}}{V^{walk}}\right) \end{cases} \quad (15)$$

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 the 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 there is a decrease in travel time compared to the previous situation. 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, 2011a) and reflect a *walking* speed of 4km/h, an average car velocity of 25km/h (*non-train*) and an average *train* velocity of 33km/h.

It is noteworthy that this transport decision model is relatively simplistic. The decision rule modeled in equation (15), however, can be improved without changing the structure of the empirical approach. As an example, travel costs in either period could be modeled as a function of differences in transport costs between modes. Moreover, monetary costs of travel and buses as an additional modal choice could be modeled explicitly. While these are interesting and potentially important extensions, the simplified model described above fits the present case reasonably well. The results are also robust to the parameter choices made. I have run an extensive sensitivity analysis in which I replicate the major stages of the analysis – estimation, prediction, evaluation – for 200 combinations of transport cost parameters. It turns out that the coefficient of primary interest Ψ is close to the benchmark model for a relatively wide range of transport cost parameters. A detailed discussion is in the web appendix.

5 Results

5.1 Estimation

Spatial models

Table 1 presents the results of spatial models used to estimate the impact of accessibility on house prices in the Greater London Area. All models include the location controls discussed above. I start with a model using a simple, but well-established distance to the CBD (LU station Holborn) as an accessibility indicator 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. The next models show the gravity estimates that correspond to the spatial models denoted in (7a–c).

Throughout the estimations the hedonic estimates generally 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, either due to multicollinearity with the distance to the CBD and potentiality variables or because unobserved correlated disamenities (e.g., congestion). The omission of the amenity variable does not notably affect the other coefficient estimates. In general, hedonic estimates are very stable across all specifications. I omit them from all tables to save space, but present them in Table A1 in the appendix for the models of primary interest (3).

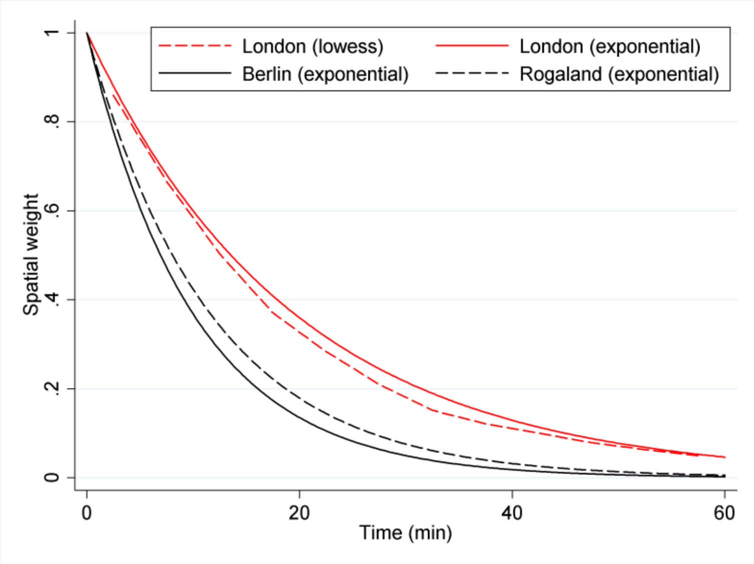
From the results in columns (1) and (2) a significantly negative relationship between prices and the distance to the CBD is evident, which is in line with standard predictions for monocentric urban economies (e.g. Alonso, 1964; Mills, 1972; Muth, 1969). On average, each 1km increase in distance is associated with a decline in prices of about 2.4%. A significant proximity effect is also found for LU/DLR stations within 2km (1.6% per km) and beyond this threshold (1.1%). This finding is in line with a consolidated body of evidence pointing to significant property price effects of urban transport. 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 of interest (α_1 and α_2) are positive and significant, which means feasible. It's noteworthy that 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 0.38 SD increase in prices, more than for any other structural or location variable. For comparison, the distance to CBD variable in (1) and (2) yields a standardized coefficient of about 0.25.

The estimated decay parameter (α_2) of 0.051 is roughly within the range found in previous studies where similar measures yielded parameters of about 0.1 (Ahlfeldt, 2011a) and 0.086 (Osland & Thorsen, 2008). The estimated implicit decay function is depicted in Figure 1 in comparison to previous evidence. Notably, the spatial decay implied by the exponential function is closely aligned with the (smoothed) estimates from the more flexible "bin model" (equation 7b, Table 1, column 4). Both estimates suggest that the impact of employment opportunities beyond 60min travel time only exerts a marginal impact. This is in line with the distribution of commuting times in the UK. According to the British Household Panel Survey, commutes over more than 60min account for no more than about 3% of all commuting trips (Sanchis-Guarner & Lyytikäinen, 2012).

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 2.5%. As intended with the semi-log form, this point estimate translates into an elasticity that varies in the level of the employment potentiality and takes values of 0.34, 0.45 and 0.62 at the first, second (median) and third quartiles. At these levels of accessibility, which roughly correspond to distances from the CBD of 17.4, 13.5 and 10.14 km, the estimated elasticity of indirect utility with respect to accessibility ($\gamma_i = (1-\alpha)\log(P_i)/\log(a_i)$) takes values of 8.5%, 11.2% and 15.5%. These magnitudes are roughly in line with recent estimates of the agglomeration effect on firm productivity derived from the within-city distribution of economic activity (Ahlfeldt, et al., 2012; Ahlfeldt & Wendland, 2012).

To further facilitate comparison with previous studies, I re-estimate the potentiality impact in log-log form in (5). Not surprisingly, the point estimate of about 0.38 is close to the elasticity at the median of about 0.45 based on column (3) results. Again, these results are roughly within the range of previous findings for Berlin and Rogaland, where an accessibility elasticity of about 0.25 was indicated. These estimates imply an estimated elasticity of indirect utility with respect to accessibility of about 6.25% compared to the 9.5% in the London log-log model (5). 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 and potentially larger accessibility benefits.

Fig. 1 Comparison of estimated decay functions



Notes: Decay parameter estimates for Berlin and Rogaland are taken from Ahlfeldt (2011a) and Osland & Thorsen (2008). "London (exponential)" illustrates the decay function estimated in Table (1), model (3). "London lowess" visualizes the results from Table (1), model (4). To facilitate easy comparability, the coefficient estimates of the "employment bins" are rescaled so that 1 equates to the value of the potentiality level parameter $\widehat{\alpha_1}$ estimated in Table (1), model (3) before a lowess estimator is used to smooth the function.

Tab. 1 Gravity model results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	NLS	OLS	OLS	SP
Distance to the CBD	-0.024**	-0.024**				
(km)	(0.001)	(0.001)				
Km to nearest LU/DLR		-0.016**				
| distance <2 km		(0.003)				
Km to nearest LU/DLR		-0.011**				
| distance ≥2 km		(0.001)				
Emp. Potentiality			0.025**			
(α_1) (in % of total emp.)			(0.001)			
Decay Parameter (α_2)			0.051**			
			(0.002)			
Log of Employment					0.386**	
Potentiality					(0.008)	
Sig. of $f(\log(\widehat{a_\iota}))$				**		**
Structural Controls	YES	YES	YES	YES	YES	YES
Location Controls	YES	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES	YES
Employment Bins				YES		
Observations	60748	60748	60748	60748	60748	60747
R2	0.7	0.7	0.72	0.72	0.71	0.72

Notes: Dependent variable is log of purchasing price in all models. Full estimation 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 significance at the 10/5/1% level.

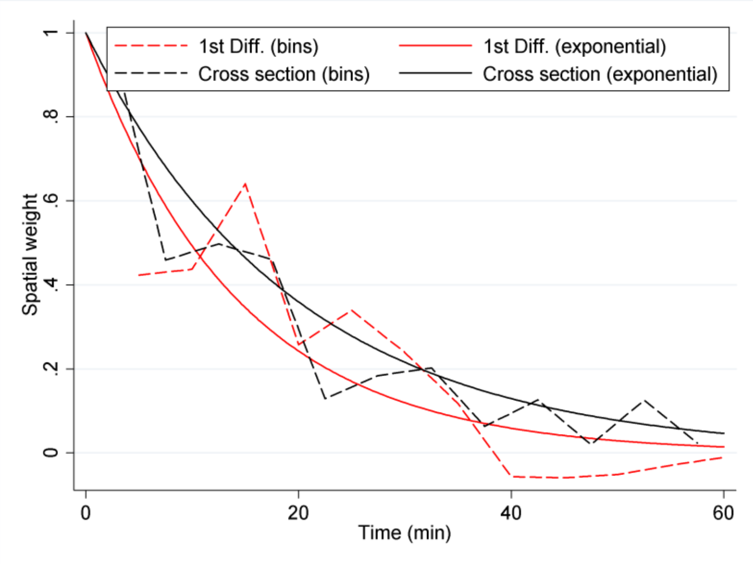
As discussed, the semi-log benchmark specification (equation 7a, Table 1, 3) is favored over a log-linear functional form due to the likely sorting of households with stronger accessibility preferences into more accessible areas. It can be demonstrated that the implied elasticities of indirect utility with respect to accessibility ($\gamma_i = (1-\alpha)\log(P_i)/\log(a_i)$) at varying levels of (log) accessibility based on the semi-log (3) and semi-parametric (6) models follow each other closely. This suggests that the semi-log benchmark model provides a decent fit to the data and provides useful parameter estimates for the prediction of the transport capitalization effects.

While not the main focus of this study, a comparison of the local accessibility elasticity (γ_i) and the local population composition yields interesting insights into heterogeneity in perceived accessibility benefits and respective spatial sorting of household types. A second-stage analysis as described in equation (8) suggest that for the average household (average of adult household members of 44.3 years, yearly household income of £37,723, average qualification) a doubling in access to local labor markets increases utility by about 12.2%. This corresponds to the equivalent of an increase in monthly income of £383 or about £9.6 per return trip, assuming that a the two-worker household makes 40 work trips per month, and the reduction in trip length is proportionate to the increase in overall accessibility. The willingness to pay for accessibility decreases in age and income, but increases in qualification, which is in line with some stylized facts observed across many cities. With increasing income, *ceteris paribus*, there is a tendency for households to live at more suburban locations while the young and highly qualified, sometimes referred to as the "creative class", are attracted to central areas with better access to job concentrations and professional and social networks. Details of the functional form evaluation and the second-stage analysis are in the web appendix (section 3.1).

Spatiotemporal models

The results from the spatial models discussed above can be validated and complemented by making explicit use of the available variation in the bilateral travel times before and after the transport innovations. This is an important contribution to the gravity capitalization literature, which has mainly focused on cross-sectional variation. With specification 9a estimated using a non-linear least squares estimator (NLS) the spatial scope of the underlying externalities reflected in the decay parameter α_2 can be identified from the changes in bilateral connectivity while holding all unobservable time-invariant location characteristics constant. Figure 2 compares the decay functions estimated from the innovations model to the cross-sectional estimates (conditional on location controls) presented above (Figure 1 & Table 1, columns 3 and 4). I make the comparison using both the exponential decay function as well as the more flexible configuration based on travel time "employment bins" (equation 9b). Baseline results for both 1st difference models are in the appendix. Reassuringly, the decay function is estimated relatively consistently despite the notable differences in the empirical approaches.

Fig. 2 Estimated spatial weight function –1st. difference vs. cross section



Notes: "Cross section (exponential)" illustrates the decay function estimated in Table (1), model (3). "Cross section (bin)" visualizes the results from Table (1), model (4). "1st Diff. (exponential)" and 1st Diff. (bin) similarly refer to columns (1) and (2) of Table A3 in the appendix. As in Figure 1, the coefficient estimates of "employment bins" are rescaled so that 1 equates to the value of the respective potentiality level parameters $\widehat{\alpha_1}$.

A typical concern regarding the capitalization effects of new infrastructures is that they may not follow a discrete adjustment path, e.g., due to anticipation effects, transaction costs in spatial arbitrage or irrational exuberance. Figure 3 plots a hedonic index of the capitalization effects according to equation 10. From the index, a relatively sharp adjustment following 1999, the opening year of the new line, is evident. This pattern supports the argument raised by GM that limited anticipation effects should be expected in areas with high owner occupancy. It is further notable that the treatment effect identified from the change in accessibility due to the new infrastructures is close to the one estimated in the spatial benchmark model (0.025, upper red line).

Fig. 3 Appreciation index

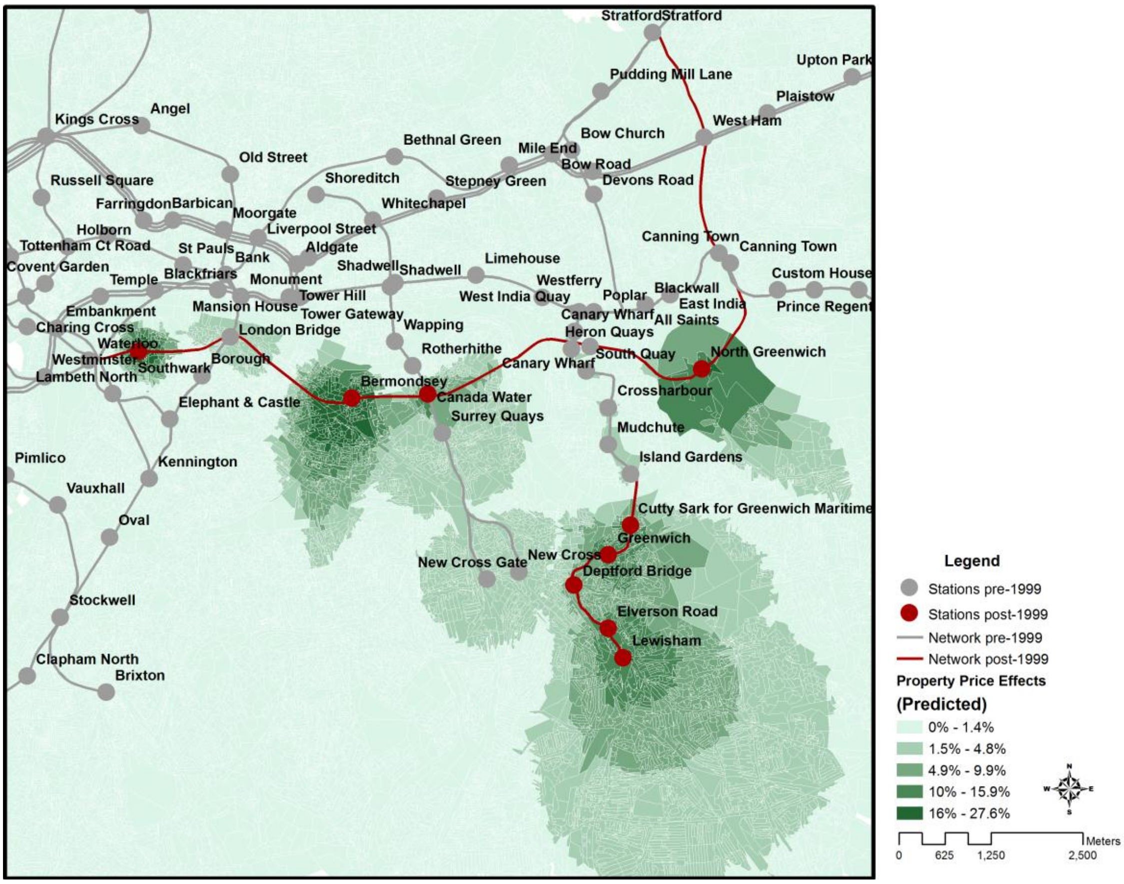
Notes: Time-varying treatment effects are estimated according to specification (11) using ward level fixed effects and standard errors clustered on wards. The black solid line shows the hedonic treatment index relative to the base year 1999. Black dashed lines show the 95% confidence interval. Treatment effects are in log (diff) scale.

5.2 Prediction and evaluation

Prediction

The results presented so far suggest that the semi-log benchmark model with an exponential transport cost function provides a decent fit for the data. Based on the estimated parameters from Table 1, (3) and the transport decision rule stated in equation (15) the model predictions for the property price effects of the 1999 Jubilee Line and DLR extension can be derived according to equation (11). 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 4. 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. 4 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. Nevertheless, it can be demonstrated that the relationship between predicted price effects and changes in station described in equation (12), on average, is closed the one identified by GM based on actual property price adjustments. A detailed analysis is available in section 3.2 in the web appendix.

Evaluation

Table 2 provides empirical estimates of the relationship between predicted and observed property price changes following the transport innovation. Columns (1–4) show the results of the quasi-panel specification (14) controlling for observable property features and unobservable time-invariant characteristics at the ward (1–2) or postcode (3–4) level. In each case I report the results using a distance to nearest station treatment for the purpose of comparability with GM (1 and 3) and the predicted property price treatment (2 and 4) as defined in equation (14). Columns (5) and (6) provide corresponding results from a repeated sales transport innovations model (equations 13).

The different specifications yield a consistent pattern. Reductions in distance to the nearest stations are associated with an increase in property prices if the outcome distance is less than 2km. In the more demanding specifications (3 and 5) a reduction in station distance by 1km is associated with a positive property price effect of about 4.8%, which is close to the findings by GM. Consistently, there are no positive station effects beyond 2km. To the contrary, the treatment coefficient is even positive and significant, likely revealing correlated unobserved changes in the city structure.

Of course, the specifications of primary interest in the context of this analysis are those using the gravity accessibility variable. The coefficient of interest $\widehat{\Psi}$ is positive, significant and reasonably close to 1 in all specifications and particularly close to 1 in the more demanding specifications with postcode fixed effects (4 and 6). In the web appendix I present several alterations of the baseline models. The estimated parameter $\widehat{\Psi}$ remains remarkably robust to significant variations in the treatment period and the control group (using spatial and propensity score matching). An alternative prediction exercise, based on the conventional distance-to-station treatment effects results, severely understates the degree of property price adjustment. An extensive sensitivity analysis shows that the efficiency of the prediction is relatively insensitive to the assumed transport cost parameters in (15). Finally, the results are supported by a difference-in-difference comparison of predicted and observed changes in mean property prices at locations close to or further away of newly opening stations.

At the very core of the research question, these results indicate that the presented gravity-based approach does a good job in predicting property price changes following a transport innovation using information that was available prior to the occurrence.

Tab. 2 Transport innovations model and predicted property effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Quasi-Panel	Quasi-Panel	Quasi-Panel	Quasi-Panel	Repeated Sales	Repeated Sales
Δkm to nearest LU/DLR	-0.057*		-0.048**		-0.048**	
| outcome distance <2 km	(0.023)		(0.012)		(0.011)	
Δkm to nearest LU/DLR	0.019**		0.017**		0.033**	
| distance ≥2 km	(0.006)		(0.004)		(0.004)	
Predicted effects$(\widehat{\Psi})$		1.137**		0.962**		0.951**
$\Delta\widehat{\log(P)}$		(0.339)		(0.394)		(0.226)
Structural controls	YES	YES	YES	YES	YES	YES
Year Effects (YE)	YES	YES	YES	YES	YES	YES
Location Fixed Effects	Ward	Ward	Post Code	Post Code	Post Code	Post Code
Location Contr. x YE	YES	YES	YES	YES		
Distance to CBD×Trend					YES	YES
Observations	131,042	131,042	131,042	131,042	15,263	15,263
R-squared	0.9	0.9	0.97	0.97	0.7	0.7

Notes: Dependent variable is log of property prices per square meter floor space. Standard errors (in parentheses) are clustered in (1-4), robust in (5) and bootstrapped in (6). +/*/** denote significance at the 10/5/1% level.

6 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 more efficiently predict the property price effects of transport innovations. 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 costs – here incurred in the form of travel time – between each pair of locations in the city.

This approach has several advantages over a more conventional accessibility modeling. The model accounts for the network dimension of rail-based transport systems by addressing the 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. Using the 1999 Jubilee Line and DLR extension in London as a natural experiment, this relatively simple and straightforward partial equilibrium approach is shown to have overall good predictive power. In the subject case, effective property transaction prices on average adjust almost one-to-one to the model predictions. The predictions are also in line with observable distance-to-station effects identified in a GM type transport innovations model.

Besides these core results, this study contributes to the transport capitalization literature with a number of important findings. First, it frames the empirical treatment of an employment gravity variable in a house price capitalization equation by a simple bid-rent theory that facilitates an economic interpretation of the parameter estimates. The results indicate an elasticity of indirect utility with respect to (labor market) accessibility of about 12% for an average household. The elasticity is within the range of within-city estimates of the effect of density on firm productivity. For the average household a doubling of labor market access yields a utility effect that is equivalent to an increase in monthly income by £383 (2001 prices). Wealthier and older (better qualified) households tend to derive a relatively lower (higher) utility. Second, a flexible empirical specification supports the convexity in the spatial decay in the impact of nearby economic activity implied by an exponential cost function that is typically assumed a priori in empirical and theoretical research. Third, a specification with time-varying treatments indicates that the capitalization of transport effects occurred relatively quickly following the opening of the new lines. This finding supports the notion by GM who argue that anticipation effects are unlikely in an environment where most properties are owned by owner occupiers. Fourth, to the best of my knowledge this is the first study to present estimates on the spatial scope in labor market effects from house price capitalization effects where the identification comes from changes in the bilateral connectivity in city regions due to transport improvements.

Altogether, the results indicate that gravity accessibility variables, when incorporating transport infrastructure and competing transport modes, represent a useful tool to model accessibility. They thus qualify as a starting point for the assessment of expected property price effects during the preliminary stages of transport planning. Given the explanatory and predictive powers on the one hand, and the relatively simple implementation on the other, I suggest the strategy presented as an ingredient in (social) cost-benefit analyses when the potential for compensation by benefiting landlords or property tax revenues needs evaluation. Taking mean housing prices at the output area level 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 £716 million —in 1999 prices and for residential properties only (see appendix for details). Backed up by *ex-post* empirical evidence, such an increase in property value could, in principle, be levied on properties bought before the announcement and sold after completion of a new infrastructure. The levy would at least not evidently distort the effects on value it attempts to capture.

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, additional modal choices and more complex transport decisions rules into the cost matrices. With some modifications, the presented approach could be extended to a range of transport innovations that affect bilateral transport costs between urban locations as well as commercial property prices and the underlying agglomeration economies, although further sensitivity checks seem warranted.

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Technical appendix to: If we build it, will they pay? Predicting property price effects of transport innovations*

Version: *October 2012*

1 Introduction

This technical appendix complements the main paper mainly by providing complementary evidence. It is not designed to stand alone or to replace the main paper. Sections 2 present details on the data and some background on the case study. Section 3 provides an extended estimation output for the models discussed in the main paper. Section 4 presents robustness checks that are not discussed in depth in the paper. Finally, section 5 presents the results of a sensitivity analysis, which evaluates the efficiency of the prediction with respect to varying assumed transport cost parameters.

2 Background & Data

The Jubilee Line and DLR extension

For the reasons discussed in the introduction of the main text, I focus on the same transport innovation as Gibbons and Machin (2005) (henceforth 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

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* I thank seminar and conference participants at Lancaster University, TU-Dresden and the ERSA conference in Barcelona and especially Nathaniel Baum-Snow, Paul Cheshire, Steve Gibbons, Georg Hirte, Liv Osland, Rob Simmons and Bernhard Wieland for helpful comments and suggestions. Felix Weinhardt provided valuable support with the KS2 data. I also thank Eric Sheppard (the editor) and three anonymous referees for helpful comments and suggestions.

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 of the 2012 Olympics main campus. With a total project cost of about £3.5 billion for about a roughly 16km extension, GM consider this project to be 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 4.3km and five new stations toward Lewisham, crossing the River Thames underground. The new sections are depicted in Figure 4 in the main text. For further details I refer to GM.

Data

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 and has also been used by GM. The study period considered in this analysis ranges from January 1995 to July 2008 (as opposed to 1997–2002 in GM). 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 the output area level. 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]

I use three more neighborhood variables in the second stage analysis of the main text (section 5.1): First, a model-based estimate at the ward level published by the office of Neighbourhood Statistics. Second, an age index (*AI*) that is computed based on the mean of age intervals (*MA*) and the respective proportions of local population (s_a) per output area as given in the 2001 census:

$$AI = \sum_{a} s_a MA$$

Third, a qualification index (*QI*), which is constructed as follows for each output area where s_q is the qualification score and p_q the population within a qualification category (q) defined in the 2001 census:

$$QI = \sum_{q} s_q \frac{p_q}{\sum_q p_q}$$

The other variables include a vector of *location controls,* which I will refer to in several tables. The vector includes the distance to the nearest historic house, landmark, museum or religious site, the shortest distance to the national rail network, an indicator variable for 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 in the whole (output area) population.

3 Baseline results

This section is designed to complement section 5 in the main text by providing an extended presentation and discussion of estimates in the main paper.

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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.

3.1 Estimation

Hedonic estimates

Throughout section 5 of the main paper I have restricted the presentation of the empirical results to the main variables of interest. Table A1 shows the hedonics estimates omitted in the main text for selected models of interest. The first column refers to the cross-sectional benchmark model, which restricts the sample to observations before the intervention and serves as a starting point for the prediction exercise (Table 1, column 3). Columns (2) and (3) show extended results for the transport innovations models by Ahlfeldt (2011b) and Gibbons & Machin (2005) used to evaluate the predictive power of benchmark model (Table 2). Column (2) presents results using the full sample and the quasi-panel (with postcode fixed effects) methodology (Table 2, column 4), while column (3) refers to the (postcode) repeated sales model (Table 2, column 6).

The hedonic results offer a reassuring degree of stability across different estimation techniques. Property prices generally increase with the size of a property measured and with the number of bedrooms, bathrooms and the total floor size in square meters. The effects are stable across the specifications except for the conditional impact of an additional bathroom, which is considerably larger in the cross-sectional model compared to the two intervention models that control for unobserved property characteristics at the postcode level. A possible explanation is that in the cross-sectional model, the number of bathrooms captures the effects of unobserved housing quality. New properties, which sell for the first time, sell at a premium. Conditional on that, property prices tend to increase with property age, despite at a decreasing rate. These results are in line with recent evidence on the value of historic buildings in England (Ahlfeldt, Holman, & Wendland, 2012). Property prices also increase in the availability of central heating systems and attached parking spaces. Consistently across all model specifications, detached, semi-detached properties as well as cottages or bungalows sell at significant premiums compared to the base category of flats. Not surprisingly, leasehold properties, all else equal, sell at discounts compare to freehold.

Tab. A1 Hedonic estimates

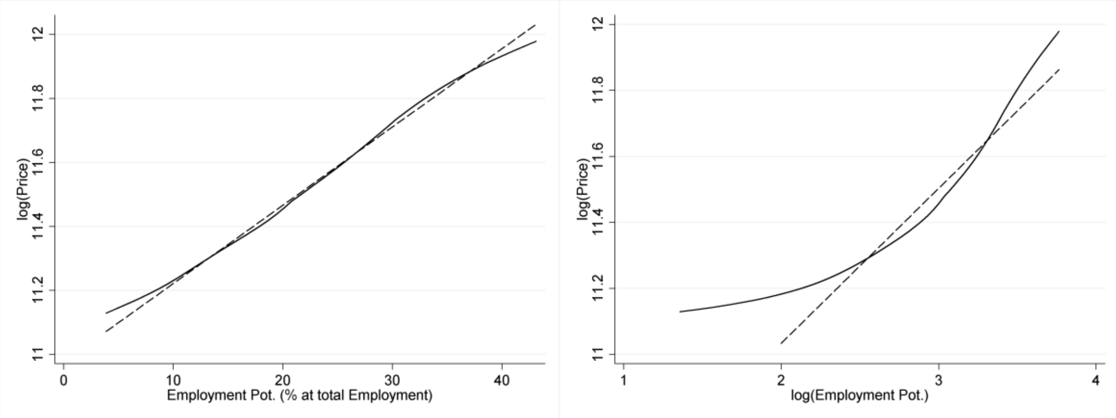
	(1)		(2)		(3)	
	Cross Sectional		Quasi-Panel		Repeated Sales	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Number of bedrooms	0.186**	0.000	0.174**	0.002	0.169**	0.003
Number of bathrooms	0.237**	0.006	0.038**	0.003	0.039**	0.005
Floor size (m^2)	0.000**	0	0.000**	0	0.000**	0
Age (years)	0.002**	0	0.001**	0	0.001**	0
Age squared	-0.000**	0	-0.000**	0	-0.000**	0
Full central heating	0.135**	0.004	0.089**	0.004	0.108**	0.007
Partial central heating	0.049**	0.006	0.044**	0.005	0.073**	0.009
Garage	0.107**	0.004	0.044**	0.003	0.049**	0.005
Parking space	0.043**	0.004	0.021**	0.003	0.010+	0.006
Detached property	0.356**	0.01	0.225**	0.009	0.217**	0.012
Semi-detached property	0.081**	0.007	0.112**	0.006	0.083**	0.009
Terraced property	-0.021**	0.007	0.088**	0.006	0.059**	0.009
Cottage or bungalow	0.220**	0.014	0.176**	0.013	0.136**	0.02
Property is new	0.198**	0.012	0.128**	0.01	0.156**	0.016
Property sells under leasehold	-0.169**	0.007	-0.145**	0.006	-0.186**	0.01
Gravity Accessibility Variable	YES		YES		YES	
Year Effects (YE)	YES		YES		YES	
Postcode Effects			YES		YES	
Location Controls	YES					
Location Controls x YE			YES			
Distance to CBD x Trend					YES	
Period	1995-1999		1995-2008		1995-1998/ 2000-2008	
Observations	60,748		131,042		15,259	
R-squared	0.72		0.97		0.72	

Notes: Depended variable is log of price per square meter in all models. Models correspond to Table 1 (3) and Table 2(4 and 6). Standard errors (S.E.) are clustered on postcodes in (1) and (2) and bootstrapped in (3). +/*/*** denote significance at the 10/5/1% level.

Functional form and second stage-analysis

As argued in the main paper (section 2), the accessibility gradient should be expected to take a convex functional from, which supports the semi-log over the log-log form, although other convex forms are theoretically possible. To evaluate how distinct functional forms fit the data, I plot the (conditional) non-linear relationship between prices and the gravity accessibility variable estimated using the difference-based semi-parametric technique by Lokshin (2006). Figure A1 shows the relationship for the semi-parametric version of the benchmark model (Table 1, column 6) using the gravity variable in levels (left) and a semi-parametric version of the log-linear specification (as in Table 1, column 5, right). From Figure A1 it is evident that the log-linear model (right) shows the expected degree of convexity while the semi-log model (left) yields a non-linear gradient that is closely aligned with a linear fit (dashed line).

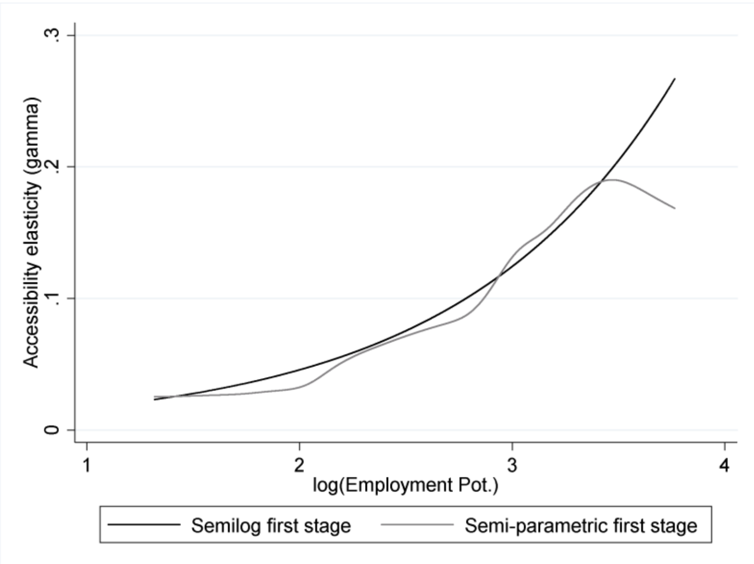
Fig. A1 Partial price-accessibility correlations – semi-log vs. log-log



Notes: Graphs illustrate semi-parametric estimates using (linearized versions of) models (3, semi-log, left) and (4, log-log, right) from Table 1 as a baseline. Semi-parametric lowess estimates use the Lokshin (2006) technique.

Figure A2 plots the implied elasticities of indirect utility with respect to accessibility ($\gamma_i = (1-\alpha)\log(P_i)/\log(a_i)$) at varying levels of (log) accessibility based on the semi-log and semi-parametric models (see figure notes for details). The graphs reveal at least two notable features. First, the (marginal) value of (log) accessibility increases at an increasing rate. Overall, the results are aligned fairly well, except for the section of highest accessibility, where the semi-log model slightly overestimates the accessibility benefit. So Figure A2, again, suggests that the semi-log functional form is a reasonable approximation of the convex function and should be favored over a log-linear model.

Fig. A2 Estimated accessibility elasticity



Notes: The indirect utility with respect to accessibility at location i is computed as $\gamma_i = (1-\alpha) \times \hat{a}_i \times a_i)$ for the semi-log estimates and as $\gamma_i = (1-\alpha)f'(a_i)$ for the semi-parametric estimates. The function $f(.)$ is estimated using the Lokshin (2006) differencing technique. $f'(.)$ is approximated as the local slope of the gradient using locally weighted regressions with a standard Gaussian kernel and a bandwidth of 0.3.

The convexity of the willingness-to-pay function revealed in Figure A2 is an important insight with respect to the main objective of this study: predicting the impact of transport innovations based on cross-sectional gravity estimates, which requires a decent fit of the employed functional form to the data. While not the main focus of this study, a comparison of the local accessibility elasticity (γ_i) and the local population composition yields interesting insights into heterogeneity in perceived accessibility benefits and respective spatial sorting of household types. Table A2 provides the results of a simple second-stage analysis as described in equation (8) based on the semi-log (1) and semi-parametric (2) estimates. The results suggest that for the average household (average age of adult household members of 44.3 years, yearly household income of £37,723, average qualification) a doubling in access to local labor markets increases utility by about 12.2%. This corresponds to the equivalent of an increase in monthly income of £383 or about £9.6 per return trip, assuming that a the two-worker household makes 40 work trips per month, and the reduction in trip length is proportionate to the increase in overall accessibility.

The results further point to significant correlations between the accessibility elasticity and selected socio-economic characteristics. A one S.D. increase in the local average household income is associated with a decrease in the accessibility effect by about 1.5 percentage points (about 12% relative to the 12.2% baseline). A similar increase in average household age similarly reduces the accessibility effect by about 0.5 percentage points (4%). The largest correlation is found with the qualification score. A one S.D. increase in the qualification index is associated with an increase in the accessibility parameter by 4 percentage points (about 30%). These findings are in line with some stylized facts observed across many cities. With increasing income, *ceteris paribus*, there is a tendency for households to live at more suburban locations while the young and highly qualified, sometimes referred to as the “creative class”, are attracted to central areas with better access to job concentrations and professional and social networks.

Tab A2 Estimated accessibility elasticity and socio-demographic features

	(1) Semi-log first stage		(2) Semi-parametric first stage	
Average yearly household income estimate in 1000P	-0.002***	(0.000)	-0.002***	(0.000)
Qualification index	0.088***	(0.001)	0.086***	(0.001)
Age index (average age of adult population)	-0.001***	(0.000)	-0.001***	(0.000)
Constant	0.122***	(0.000)	0.118***	(0.000)
Observations	60748		60748	
R^2	0.598		0.602	

Notes: Standard errors in parentheses. Explanatory variables rescaled to zero mean. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Spatiotemporal models

Figure 2 in the main paper illustrates the spatial decay in labor market externalities estimated using variation from changes in bilateral transport times following the inauguration of the new LU/DLR sections. Table A3 tabulates the results for the exponential transport cost function (1) and the employment bin specification (2). Comparing column (1) results of the benchmark model reveals that the estimated decay is roughly within the same range (as illustrated in Figure 2), though slightly steeper in the spatiotemporal model (reflected by the larger decay parameter α_2). While the level parameter (α_1) is significantly larger (0.062 vs. 0.025) it has to be noted that the two estimates are not directly comparable due to the different scales of the variation in (gravity) accessibility variable in the cross-section (Table 1, column 3) and the 1st-difference model (Table A3). Take as an example the area around the LU station Bermondsey, which receives the highest absolute upgrade in terms of accessibility. Travel time weighted access to employment $\left(\sum_j E_j / \sum_j E_j \, \Delta\left(e^{-\alpha_2 TT_{ij}}\right)\right)$ at a location near to the station increases by about 10 percentage points (in terms of access to total employment in the area). Given the point estimate (α_1) in Table A3, column (1), this increase implies an indirect elasticity of utility with respect to accessibility $\left(\gamma_i = (1-\alpha)(\partial\Delta\log(R_i)/\partial\Delta\log(a_i))\right)$ of 0.155. The cross-sectional parameter from the benchmark model (Table 1, column 3) at the post-intervention level of accessibility (25 percent of total employment) implies a similar elasticity (0.152).

Tab. A3 Time difference decay models

	(1)		(2)	
	Coeff.	S.E.	Coeff.	S.E.
Employment Potentiality (α_1) (in % of total emp.)	0.062	0.009		
Decay Parameter (α_2)	0.063**	0.012		
Structural controls	YES		YES	
Year Effects	YES		YES	
Postcode effects	YES		YES	
"Employment bins"			YES	
Period	≤1998/ ≥2000		≤1998 / ≥2000	
Observations	15,259		15,259	
R^2	0.681		0.721	

Notes: Dependent variable is log of purchasing price per square meter floor space in all models. Standard errors (in parenthesis) are clustered on postcodes except for the decay parameter in (1). +/*/** denote significance at the 10/5/1% level.

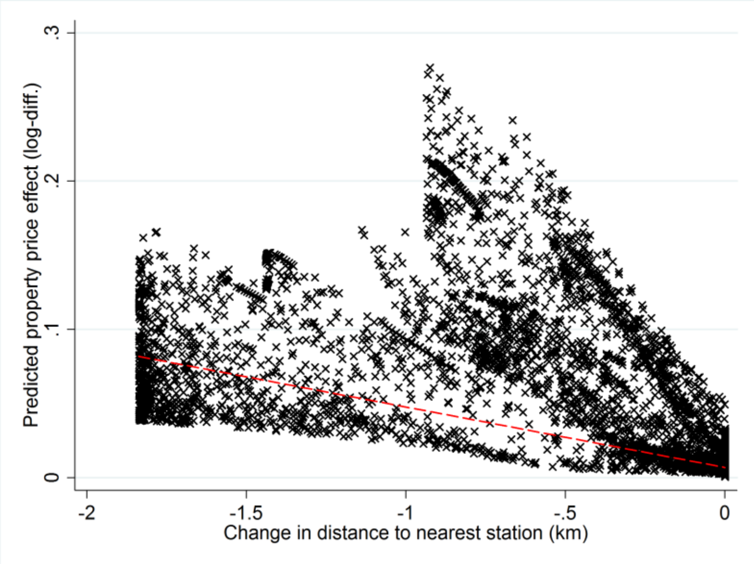
3.2 Prediction

Predicted effects and change in station distance

Figure 4 in the main text show the predicted property price effects of the Jubilee Line and DLR extension by postcodes. When plotting the predicted postcode effects against the experienced change in distance to nearest station it becomes evident that the average treatment effect (indicated by the dashed line) masks a significant degree of heterogeneity (see Figure A3). Acknowledging the spline in the station effect found by GM, I restrict the sample to postcodes that are within 2km of an 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. A3 Predicted Effects vs. Change in Distance to Station



Notes: Own illustration. Sample restricted to postcodes within 2km of a station in 2000.

Table A4 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 (1) and without (2) considering the linear spline at 2km identified by GM. The predictions produce marginal price effects that are within the range provided by GM, although they are somewhat at the upper boundary.

Tab. A4: Predicted Effects vs. Change in Distance to Station

	(1)		(2)	
	Coeff.	S.E.	Coeff.	S.E.
Δkm to nearest LU/DLR	-0.041**	(0.001)		
Δkm to nearest LU/DLR | distance ≤2 km			-0.067**	(0.001)
Δkm to nearest LU/DLR | distance >2 km			-0.008**	(0)
Unit	Post codes		Post codes	
Observations	30,978		30,978	
R2	0.28		0.46	

Notes: Depended variable is predicted change in property prices. +/*/** denote significance at the 10/5/1% level.

Evaluation

To provide a descriptive difference-in-difference comparison of observed and predicted price adjustments, I assign postcodes to the treatment group if they experience a reduction in nearest station distance and the outcome distance is less than 2km $\left(d_i^{POST} - d_i^{PRE} < 0 \;\& d_i^{POST} \leq 2\text{km}\right)$. 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.

Table A5 compares the observed and predicted changes in mean (log) prices for the treatment and control group. 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 140% over an 8.5-year period. In line with GM's findings, the mean growth in the treatment group is larger than in the control group. The 9.5% effect is very close to the one found by GM (0.089). A regression-based t-test, which is equivalent to a difference-in-difference (DD) estimate, rejects the H0 of a zero-difference (3).[2] The respective DD estimate based on the predicted price effects yields a somewhat lower treatment effect of 5.7% (6). It is notable that this estimate is very close to GM's matched (based on property and location characteristics) DD estimate (6.1%).

Tab. A5 Descriptive analysis of treatment effects

	Current			Predicted		
	Treatment (1)	Control (2)	DD (3)	Treatment (4)	Control (5)	DD (6)
Δlog(P)	0.982	0.887	0.095**	0.057	0.000	0.057**
	(0.411)	(0.390)	(0.024)	(0.039)	(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.

Aggregate effects

The empirical strategy suggested in the main paper can be used to provide an *ex-ante* assessment of an increase in aggregated land value caused by a planned transport infrastructure project. For a given year (e.g. 1999) the aggregated impact on property value (AI) can be computed in a back of the envelope calculation by multiplying the predicted treatment effect by the average local price level $\left(\hat{P}_o^{1999}\right)$ and the respective housing stock (H_o, based on the 2001 census), where o indicates an output area.

$$AI = \sum\nolimits_o \widehat{\alpha_1} \times \left(\sum\nolimits_j \frac{E_j}{\sum_j E_j}\left(e^{-\widehat{\alpha_2}TT_{oj}^{POST}} - e^{-\widehat{\alpha_2}TT_{oj}^{PRE}}\right)\right) \times \hat{P}_o^{1999} \times H_o$$

[2] 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 $DD = \left(\log\left(\overline{P_T^{POST}}\right) - \log\left(\overline{P_T^{PRE}}\right)\right) - \left(\log\left(\overline{P_C^{POST}}\right) - \log\left(\overline{P_C^{PRE}}\right)\right)$.

An estimate of the average local price level in a given year can be recovered from an auxiliary regression of property prices on output area ϕ_o and year fixed effects φ_t, where 1999 is omitted as a based category. Only property transactions preceding the transport innovation are considered in this empirical example.

$$\log(P_{it}) = \phi_o + \sum_{t \neq 1999} \varphi_t + \varepsilon_{it}$$

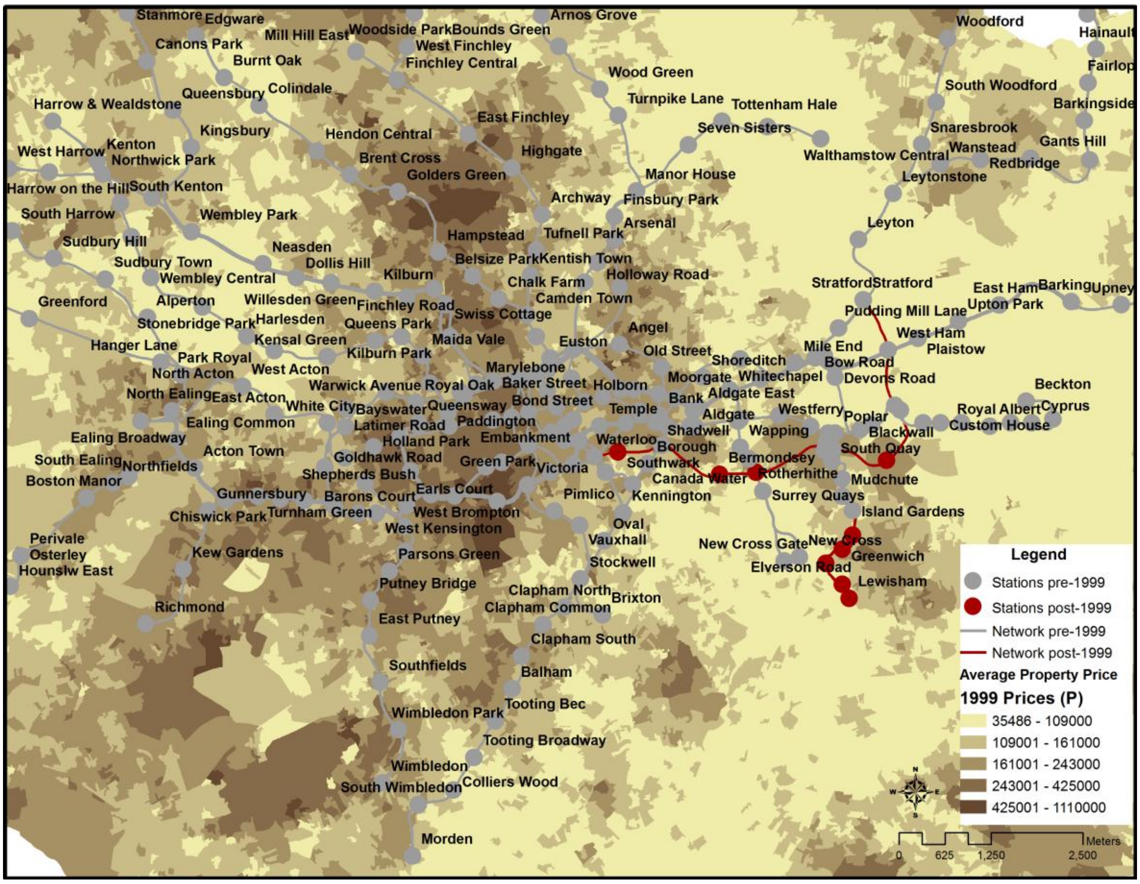
The average property price at output area in 1999 can then be recovered from the output area fixed effects.

$$\hat{P}_o^{1999} = \mathrm{e}^{\phi_o}$$

I fill some gaps for output areas with missing transactions by application of a standard IDW spatial interpolation technique. The resulting property price map is illustrated in Figure A4.

Using the estimated accessibility effects from the benchmark model (main text Table 1, column 3) the procedure yields an aggregated effect of the LU/DLR extension of about £716million –in 1999 prices and for residential property only. It is notable that this value inflates with house price appreciation. This is important to consider since property tax revenues increase with housing values. Also, compensations by landlords may realistically be charged after a property has been sold and the benefits have been capitalized, and thus with some lag. London during the observation period is a particularly impressive example due to stark increases in housing values. The estimated year effects in Table 2, column 4 (main text) model indicate that house prices, on average, have increased by about 230% from 1999 to 2007 (exp(1.19)-1), which is in line with the official Nationwide house price index for London. Assuming similar inflation of house prices across the metropolitan area, this corresponds to an increase in the aggraded impact to about £2.4million.

Fig. A4 Estimated 1999 property prices by output area



Notes: Own calculation and illustration.

4 Robustness checks

This section complements Table 2 in the main text by presenting and discussing variations of the specifications used. The aim is to evaluate the robustness of the findings presented in the main text. The results discussed in the remainder of the section are presented in Table A6.

In columns (1) and (2), I use predicted property price changes based on the cross-sectional distance to station estimates from main text Table 1, column (2). When using changes in station distance where the outcome distance is less than 2km alone, price adjustments, on average, are underestimated substantially (as indicated by a $\hat{\Psi}$ substantially larger than one). Including outcome distances larger than 2km reduces the adjustment coefficient, which even becomes negative, though not statistically distinguishable from zero. The relative predictive power of the gravity approach also becomes evident when introducing predicted price effects and changes in station distance (including a spline at 2km) jointly (column 3) into a model. The effect of station proximity is reduced to virtually zero, indicating that the gravity variable captures most of the variation that is systematically related to distance to the station. This result resembles Ahlfeldt's (2011a) findings from a cross-sectional study of accessibility capitalization effects in Berlin, Germany.

A typical concern in the related literature is that house price capitalization of new infrastructures may not follow a discrete adjustment path, e.g. due to anticipation effects, transaction costs in spatial arbitrage or irrational exuberance. Figure 3 in the main text suggests a relatively sharp adjustment following 1999, the opening year of the new line. This pattern supports the argument brought forth by GM that limited anticipation effects should be expected in areas with high owner occupancy. While the index is relatively stable during the post period, there seems to be some noise in the estimates for the first years. To evaluate the sensitivity of the results to variations in the study period, I cancel out the effects of the years around the inauguration (4) and the first two years excluded in GM analysis (5) on the treatment estimate by introducing interactive terms of the treatment variable and the respective year dummies in columns (4) and (5).

Another typical concern in quasi-experimental research designs where the treatment effect is identified from a comparison of individuals that are exposed to differing levels of treatments is a sensitivity of results to the selection of the subjects in the control group. Throughout columns (6-8) I therefore vary the sample by a) narrowing it down to a circular area around Bermondsey station (6-7) and b) choosing matched pairs of transactions inside and outside the treatment group defined in Table A5. The propensity score matching approach is briefly discussed in the Table notes. Reassuringly, the adjustment coefficient is estimated relatively consistently across all specifications.

Tab. A6 Robustness checks and extensions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quasi-Panel	Quasi-Panel	Quasi-Panel	Quasi-Panel	Quasi-Panel	Quasi-Panel	Quasi-Panel	Quasi-Panel
Predicted effect ($\widehat{\Psi}$)	3.046**	-0.179	0.846*	0.970**	1.011**	1.094**	0.959**	0.852**
Δlog(P)	(0.747)	(0.378)	(0.395)	(0.349)	(0.26)	(0.331)	(0.308)	(0.287)
Δkm to nearest LU/DLR			-0.001					
| outcome distance <2 km			(0.022)					
Δkm to nearest LU/DLR			0.023**					
| distance ≥2 km			(0.006)					
Predicted Price Effects	ΔStation Distance: outcome dist. ≤2km	ΔStation Distance: spline at 2km outcome dist.	Potentiality	Potentiality	Potentiality	Potentiality	Potentiality	Potentiality
Cost Parameters	-	-	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark	Benchmark
Structural controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Effects (YE)	YES	YES	YES	YES	YES	YES	YES	YES
Location Fixed Effects	Post Code	Post Code	Post Code	Post Code	Post Code	Ward	Ward	Ward
Location Controls x YE	YES	YES	YES	YES	YES	YES	YES	YES
Distance to CBD×Trend				-				
Treatment (Δlog(P)) x YE	-	-	-	1998-2000	1995-1996	-	-	-
Study Area (km from Bermondsey)	All	All	All	All	All	20	15	All
Propensity Score Matching	-	-	-	-	-	-	-	Structural & location controls
Observations	131,042	131,042	131,042	131,042	131,042	109,525	75,467	4,636
R-squared	0.97	0.97	0.97	0.97	0.97	0.90	0.89	0.89

Notes: Dependent variable is change in log of property prices per square meter floor space. Standard errors (in parentheses) are clustered on post codes (1-5) or wards (6-8). Propensity score matching creates matched pairs of observations in a treatment (Δkm to nearest LU/DLR<0 & outcome distance <2 km) and a control group (rest). Propensity scores are predicted from an auxiliary logit regression of the indicator treatment variable on structural and location controls. Starting with the highest score, each observation in the treatment group is assigned to the counterpart from the control group with the closest score (that has not been assigned to another observation in the treatment group). +/*/** denote significance at the 10/5/1% level.

5 Sensitivity Analysis

In this section I present the results of a sensitivity analysis with respect to the transport cost parameters imposed in the transport decision model (equation 15 in the main text). While the parameters assumed in the benchmark models were borrowed from the literature, a considerable degree of uncertainty is often attached to the choice of these parameters. Therefore, I conduct a sensitivity analysis with regard to the chosen parameters to a) back out the appropriate parameters from a comparison of implied predicted and observable property changes and b) evaluate how sensitive the implications are with respect to the parameters chosen.

I rerun the basic stages of the empirical analysis, i.e. Table 1 (3), Table A4 (2) and Table 2 (6) 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 200 combinations of V^{walk}={1, 2, 3, ..., 10}km/h and $V^{non\text{-}train}$={11, 12, 13, ..., 30}km/h. The threshold at 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 available for access to stations and the slowest mode for direct connections between each pair of origin and destination 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.

Two conditions can be used to identify the efficient set of transport cost parameters w from a comparison of predicated and observed price adjustments. First, the deviation of the adjustment parameter in Table 2, column (6) from one should be minimized $\left(\min|\widehat{\Psi}_w - 1|\right)$. Second, the implied distance to station effect ($\hat{\xi}$, see Table A4, column 2) should be close to the one identified using the transport innovations model (see Table 2, column 5), hence $\min|\hat{\delta}_w - \hat{\xi}_w|$. I define a simple selection criterion that incorporates both conditions, in each case normalized by the respective standard deviation (σ). This criterion for each parameter combination w produces a score between 0 and 100 where 100 implies the perfect fit.

$$\Lambda_{\mathrm{w}} = \left[1 + \left(\frac{\widehat{\Psi}_w - 1}{\sigma_{(\widehat{\Psi}-1)}}\right)^2 + \left(\frac{\hat{\delta}_w - \hat{\xi}_w}{\sigma_{(\hat{\delta}-\hat{\xi})}}\right)^2\right]^{-1} \times 100$$

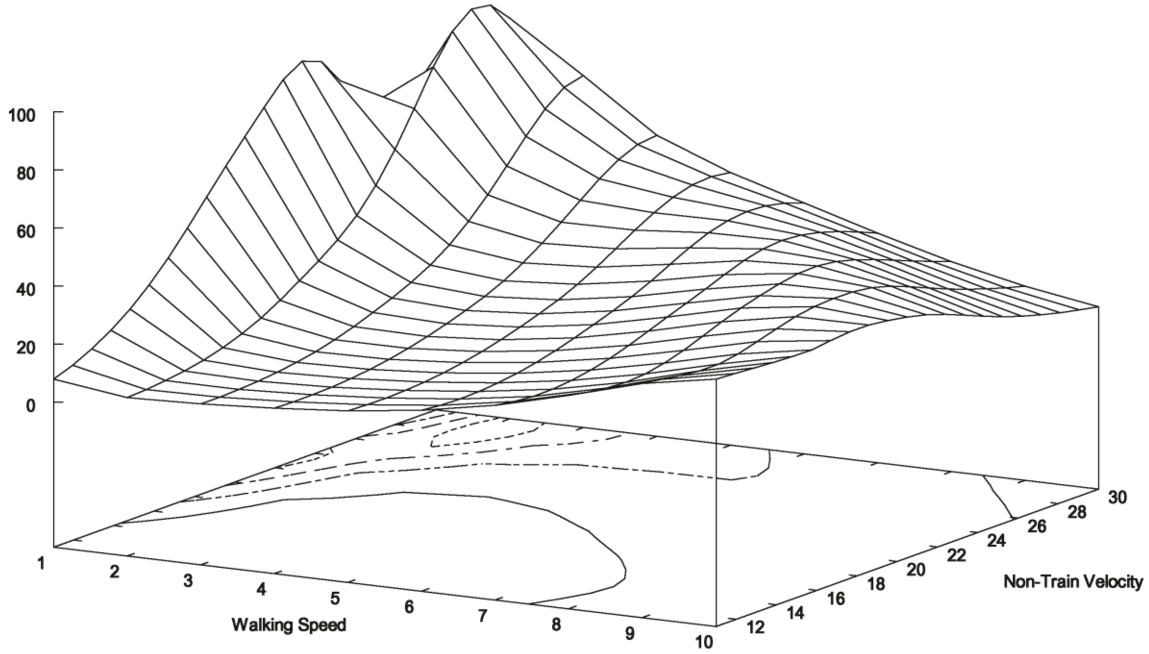
The scores resulting from the grid search are depicted in Figure A5. Note that the gravity approach proves robust in the sense that all estimated $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ parameters are feasible (positive and significant). Moreover, a model fit (in terms of R squared) is produced that exceeds the standard set by the distance-based benchmark model (Table 1, column 2) for all (relative) cost parameter combinations. Also, all estimated benchmark criteria are feasible, i.e. there is a positive (conditional) correlation of expected and predicted price effects ($\widehat{\Psi} > 0$) and a negative correlation of implied price effects and (change in) distance to station ($\hat{\xi}_w < 0$). The best fit according to the selection criterion (about 96) is actually achieved for a combination of V^{walk} 2 km/h and $V^{non\text{-}train}$ = 28 km/h, which is close to the parameters that were taken from the literature.

The relatively low walking speed is comprehensive in light of the underlying straight line distances used. Ahlfeldt & Maennig (2009) find that road distances tend to exceed straight line connections by a factor of about 1.5, implying an adjusted walking speed of about 3 km, which seems plausible taking into account typical waiting times, e.g. at signals, when crossing streets, etc. The efficient parameter combination also implies a relatively fast non-train velocity, most realistically achievable using cars (as opposed to the use of buses). The high non-train velocity indicates that relatively high velocities must be achieved using public transport to make users indifferent between the two modes.

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 reference, which still indicates a good fit compared to the station distance based prediction ($\widehat{\Psi} = 3$) ,$\widehat{\Psi}$ is close to one for basically all non-train velocities $V^{non\text{-}train}$ ≥20 km/h as long as V^{walk}≤5km/h.

While the results of the sensitivity analysis support the benchmark parameters it is obviously important to give these parameters a careful plausibility check before applying them in a forecasting model.

Fig. A5 Grid search results



Notes: Own calculation and illustration. Figure illustrate the selection scores according to the criterion Λ_{w}.

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