Journal of Transport Geography 64 (2017) 13–22

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

"*Waiting on the train*": The anticipatory (causal) effects of Crossrail in Ealing☆

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ARTICLE INFO

Keywords:
Transport intervention
Willingness-to-pay
Spatial econometrics
Difference-in-difference model

ABSTRACT

This paper estimates the willingness-to-pay for anticipated journey-time savings introduced by the Crossrail intervention in the London Borough of Ealing. Given Crossrail remains under construction, we estimate how the anticipated benefit of Crossrail's announcement enters the house price determination process. Anticipated journey-time savings should enter the home-buyer's pricing equation because these benefits are speculatively internalised even before the service becomes operational. Using a experimental method that accounts for the possibility of a spatial autoregressive process in housing values, we test the hypotheses that the announcement of a new commuter rail service generated a location premium, and that house price appreciation reflected proximity to Crossrail terminals. Our evidence suggests home-buyers significantly valued proximity to planned Crossrail terminals following the post-announcement period.

1. Introduction

Property location and value are highly interrelated. The desirability of locations are key determinants of localised variations in property price. Rail interventions that alter a location's relative accessibility will increase mobility ranges to workplaces, leisure and retail destinations (Baum-Snow and Kahn, 2000). For commuters, investments in rail access change the distribution of available employment and wage opportunities by lowering transport costs to more specialised, and potentially more productive, high-paid jobs (Gibbons and Machin, 2005). On the other hand, rail-related upgrades generate negative externalities such as visual nuisances, air pollution and transit-generated crime (Bowes and Ihlanfeldt, 2001). On this basis, assuming property markets are efficient, the value of residential housing should "reflect all the costs and benefits a location offers" (Gibbons and Machin, 2005), and the expectation of improvements in environmental conditions, such as accessibility, should be capitalised in transaction values. For these reasons, housing markets are conduits for the economic impacts of transport interventions, and provide a compelling backdrop to study the impacts of rail investments.

Standard appraisals assess the willingness-to-pay (WTP) for proximity to rail interventions by obtaining quantified measures for the economic value of rail access. Typically, journey-time savings of rail access are valued by empirical applications as shadow prices elicited by stated preferences or revealed preferences in transport mode choice (Hensher, 2010). Yet, the impacts of transport innovations are diverse, and researchers investigating rail-related interventions must situate their findings alongside wider debates in transport studies. Beyond land value changes, rail access that increases workplace density by concentrating firms generates agglomeration forces and urbanisation economies that result in productivity cost savings, knowledge spillovers and job-worker matching (Henderson, 2003; Venables, 2007). On this basis, it is tempting for governments to reiterate the wider economic benefits of transport innovations, but these impacts are not always appropriately evaluated. Transport policies that increase accessibility for some residential areas and not others will typically increase housing costs there, as these locations become desirable for workers and less desirable for non-workers (Gibbons and Machin, 2008). In this way, arguments that proposition transport as a policy lever for increasing employment are challenged by housing market processes that sort less-employable individuals into less accessible – and thus lower cost – areas (SEU, 2003). In other words, it is imperative to be aware of the labour market effects of transport interventions that are diverse, and will yield effects not fully quantified by conventional transport appraisals.

In this paper we analyse the WTP home-buyers attribute to *anticipated* passenger rail upgrades using property price to value rail access in an Outer London Borough. We consider Transport for London's (TfL) Crossrail intervention that will provide high-frequency commuter rail

☆ This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
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http://dx.doi.org/10.1016/j.jtrangeo.2017.08.004
Received 1 February 2017; Received in revised form 2 August 2017; Accepted 16 August 2017

services along 118-kilometres of double-track railway lines from Reading to Shenfield. In particular, we consider Crossrail's upgrades to service provisions along the Great Western Main Line in Ealing – an Outer London Borough in West London in which Crossrail 'passes by' to connect employment centres in the City of London to Travel-To-Work-Areas (TTWAs) east and west of the capital. A Department for Transport (DfT) study featuring rail-usage statistics from the Office of Rail Regulation found First Great Western – an inter-city and regional rail service operating through its London terminus to Oxfordshire – had the highest Passengers in Excess of Capacity (PiXC) of any London and South East rail operator[1] (DfT, 2013). Given Ealing's high PiXC scores and increasing rail patronage (2.8% growth through 2001–2011 (ONS, 2013)), there remains a need to improve rail services to meet commuter demand.

To achieve this, Crossrail was announced on 22 July 2008 by the Crossrail Act 2008 which granted Cross London Rail Links (CLRL) – now Crossrail Ltd. – the powers to construct the line which is scheduled for completion by 2019 (Crossrail, 2016d). Given Crossrail's installation promises increased journey-time savings, we expect the mere announcement to provide an exogenous change that affects property values. We expect anticipated journey-time savings to enter the utility functions of home-buyers. This is because transport interventions that reduce the friction of distance between complementary activities (so as to increase net agglomeration benefits) increase journey-time savings for firms and households, meaning neighbourhoods closer to investment areas become more likely to elicit higher property values (Grimes and Young, 2013; Vessali, 1996). In essence, this study sheds light on how housing markets anticipate planned increases in accessibility.

To date, an extensive body of literature evaluates the effect of rail interventions on real estate values for European markets (e.g.,Lochl and Axhausen, 2010; Dorantes et al., 2011; Efthymiou and Antoniou, 2013a) and US markets (e.g., Hess and Almeida, 2007; Kawamura and Mahajan, 2005; Cohen, 2010). Most papers stress the marginal effect of rail interventions varies according to their location and service-level characteristics (Dubé et al., 2011a). Cervero and Duncan (2002), for example, point out 'the impacts of transport systems on property prices are highly localised' according to the district studied. Brandt and Maennig (2012) demonstrate that, for the city of Hamburg, the value premium for proximity to public transit systems was 4.6% within 250–750 m of the nearest station. Yet, for Miami, Gatzlaff and Haurin (1997) report the absence of significant price difference for homes located near Metrorail stations and cite low substitutability among transport mode choice to explain this. Other studies demonstrate the location premium is linked to service usage, the type of clientele and carrying capacities of the rail system (Bowes and Ihlanfeldt, 2001).

Measures of accessibility have also been shown to influence the expectation of the willingness-to-pay for rail transit. Ryan (1999), for example, states that variation in property values are more directly correlated with travel time savings than with distance from transport facilities, and so incorporating a direct measure of travel time savings finds more consistent property value effects. In general, however, empirical evidence implies that accessibility to rail stations increases property values. Meta-regression studies confirm this, with Debrezion et al. (2011) finding that averaging the explanatory variable causes housing prices to increase 2.4% every 250 m closer to a station, and Mohammad et al. (2013) finding properties 501–850 m away from rail stations increased values by 8.7%. Additional reviews on the effects of rail improvements on housing prices can be found in RICS (2002) and Zhang (2009).

The UK has also received attention from researchers, although empirical findings are not conclusive by any means. In London, Gibbons and Machin (2005) found the hedonic impact of the Jubilee Line Extension (JLE) and Docklands Light Railway (DLR) construction caused property value to rise by 9.3% in affected areas between 1997 and 2001. In South Yorkshire, Henneberry (1998) found Supertram's announcement increased housing prices by 4.0% for properties situated in proximity to the light-rail system in 1988 but these value premiums had dissipated by 1996. In the case of Manchester, Forrest et al. (1996) found its housing market reacted negatively to the Metrolink intervention by depreciating property values.

Despite its theoretical soundness, the marginal effect of *anticipated* transport interventions on house prices has been little studied for rail networks, with only few notable exceptions (see Grimes and Young, 2013; McMillen and McDonald, 2004). Several papers claim the introduction of a public mass transit system requires a delay during which stakeholders speculatively internalise the effect even before the service becomes operational (Dubé et al., 2011a). We contribute to this literature by demonstrating that rail interventions positively enter the utility functions of home-buyers *even before* they have been completed. At a more general level, the paper contributes additional, causal evidence of the positive valuation of rail interventions in urban housing markets.

This paper identifies the causal effect of the intervention by adopting a difference-in-difference (DiD) estimator, avoiding many of the biases inherent in standard cross-sectional models. Relying on the "opportunistic" location of Ealing, in-between employment centres and thus not the explicit target of the policy, we consider the announcement of Crossrail-related station upgrades as a quasi-natural experiment that allows us to isolate its causal effect. In all, because serving Ealing is not the explicit goal of Crossrail, the announcement can be treated as an external shock which generates an exogenous source of variation for the study area. To refine our analysis, we further include standard controls used in housing models and control for the presence of remaining spatial autocorrelation, a usually ignored condition in this type of set-up. Overall, we find for every kilometre a house is closer to a station targeted for Crossrail upgrades, the WTP of home-buyers increases between 2.4% and 2.5%.

The remainder of the paper is organised as follows. Section 2 introduces the context of the study area and descriptive statistics relating to the data series. Section 3 motivates the specification and underlying assumptions of cross-sectional, spatial autoregressive and DiD estimators. Section 4 presents model estimation results and diagnostics. Section 5 discusses policy implications of this research. Section 6 concludes the paper.

2. Context and data

The study area comprises the London Borough of Ealing, a 55 km^2 local authority district with 338,499 inhabitants that lies inside the London Travel-To-Work-Area (TTWA) (Ealing Council, 2011). Between the 2001 and 2011 censuses, the employment-household ratio remained relatively stable ~1.3:1 with only the absolute numbers for total employment and household spaces increasing.[2] Clearly, the economic profile of Ealing reflects a relatively stable local authority district, with the average household size growing only marginally by 3.8% between the census periods. As a Low Emission Zone (LEZ), Ealing monitors strict conformity to European Union emission standards in order to reduce automobile dependency and stimulate transit-orientated developments of mixed and dense urban housing around transportation nodes. Ealing's passenger rail network is provided by National Rail (NR) and London Underground (LU). The former is a main-line rail system managed by Network Rail and operated by several private rail operating companies, whilst the latter is a metro-style

[1] In 2012, for example, Ealing's PiXC peaked at 9.6% between 08:00–08:59 relative to service provisions by Northern Rail and TransPennine Express who enjoyed comparatively lower PiXC's of 3.7% and 3.9%, respectively.

[2] Total employment and household spaces increased from 153,781 to 157,500 and 118,100 to 124,082, respectively (Office for National Statistics, 2011).

system managed by publicly-funded TfL. As of 2011, 27.3% of Ealing's working population commute via LU and NR services. Disaggregating this, approximately 22.6% rely on LU and 4.8% on NR; whereas LU aligns with the London average, NR usage sits 8.5% below this (ONS, 2013). In other words, approximately 43,039 commuters rely on rail transport to travel to work, which is instructive of the importance of rail access in this area.

Rail interventions are often 'smart growth' tools that aim to address traffic congestion and strengthen the economic viability of cities due to their high fixed costs but low marginal costs of carrying additional passengers (Cervero, 2004a; Kahn, 2007). We use the announcement of Crossrail in 2008, a new railway for London and the South East of England, to investigate how housing anticipates changes in transport policy. The project was announced by the Crossrail Act 2008, which sought to improve operational capacities of passenger rail networks by increasing the number of rail departures. Given current construction trajectories, Crossrail is scheduled for full operation by 2019. Crossrail is part of a wider regional strategy to connect employment areas such as the City of London, Canary Wharf, the West End and Heathrow Airport, and to make them more productive by increasing their overall accessibility. Crossrail pledges 10% increases to existing rail capacities of National Rail and London Underground services, with an additional 1500 commuters transported every 7.5 min during peak hours (Crossrail, 2016a). A timeline for Crossrail's planning process can be found in Table 1.

Following the Crossrail Act 2008 on 4 December 2008, TfL and the DfT signed the Crossrail Sponsors' Agreement. This arranged co-financing of the intervention (projected to cost £15.9 billion), with auxiliary funding secured from Network Rail, Heathrow Airport Holdings and the City of London, enabled by the 2011 Localism Act, which empowered the Mayor of London to implement Community Infrastructure Levies to provide Local Authorities finance-raising powers to subsidise regional infrastructure projects (Crossrail, 2016b). With the Crossrail Sponsor's Agreement sourcing funding streams, 118-km of double-track railway lines from Reading to Shenfield were commissioned alongside electrification upgrades for existing lines, urban renewal programmes and park-and-ride systems to increase multi-modal commuting towards the city (Fig. 1). For Ealing, five Crossrail terminals are planned to be installed at Southall, Hanwell, West Ealing, Ealing Broadway and Acton Main Line stations (see Figs. 1 and 2). This includes new station buildings and platform extensions to accommodate the 205 m long Crossrail trains.

In contrast to a London-wide study, we choose to limit our sample of properties within the geographical extent of Ealing. This decision is made to minimize the potential sources of endogeneity in the assignment of the treated locations. Given the stated goal of Crossrail is to connect employment centres in London and increase general accessibility, using Ealing allows us to assume the intervention as exogenous to the internal dynamics of its housing market. In other words, because serving Ealing explicitly is not the main goal of Crossrail (but rather the area is receiving Crossrail as a by-product of its location in-between employment centres) we treat the announcement of station upgrades as an external shock, a quasi-natural experiment, that provides an exogenous source of variation at the house level. Given we conceive the quasi-experimental experiment at the household rather than neighbourhood level, the exogenous shock is expected to affect housing in the neighbourhood to varying degrees. This variation in the intensity of the treatment, mediated through space and distance, allows us to recover the effects using only Ealing. Finally, Crossrail's treatment assignment to existing stations in Ealing is assumed to be independent from unobserved factors that are spatially correlated with the location of stations.

A compelling justification for choosing Ealing is also the commuter profile of the local authority *vis-a-vis* origin-destination flows. Given commuting results in a daily net change of −32,372 people (with the largest outflow of commuters to employment centres in Westminster, Hillingdon and Hounslow (ONS, 2013)), Ealing is a strong candidate as an origin of commutes, meaning there is a strong likelihood for transport improvements to significantly enter the house price determination process.

The data for the study relies almost entirely on property transaction data from the Land Registry (2016) – a non-ministerial body responsible for registering land ownership in England and Wales – for the period 2002 to 2014. The basic set contains 50,864 single-family housing transactions (31,435 pre-announcement and 19,429 post-announcement) and includes a range of property descriptors such as market value, transaction date, housing tenure, and residential addresses. Land Registry (2016) defines new build properties, for example, as housing unoccupied yet for the first time and/or completed in the last 2 years, excluding conversions. Moreover, we merge several classifications defined by Strategi (2011) as public park spaces, national parks and woodland areas into a vector for the green space variable. In all, we consider the data as a panel because houses are sold in different locations at different times. Whilst a repeat-sales data strategy was considered for removing potential sources of unobserved heterogeneity, this was decided against for two reasons. Firstly, repeat-sales shrunk the sample size too far because it only used information on property units sold more than once across the 12 year study period. Secondly, given a shrunken sample, we potentially end up with a non-random sample of Ealing's property market.

We further geocode the addresses to access the exact latitude and longitude of each house in the dataset. Geocoding allows us to augment the original database with numerous predictor variables sourced by the ONS and EDINA Digimap, and motivated by previous uses in similar applications. These variables enter the hedonic model to control for structural, locational and environmental characteristics of properties. A full list may be found in Table 2. Euclidean distance from the each property to the nearest georeferenced amenity/disamenity was calculated in QGIS (QGIS Development Team, 2016), as was the geocoding of the addresses.

Table 1
Crossrail timeline.

Time	Milestone
2005–2007	Crossrail Bill is reviewed by the Crossrail Bill Select Committee.
2008	Crossrail Act receives Royal Assent by Westminster (critical announcement date).
2014	Major civil engineering works nearing completion, including 26 miles of tunnelling.
2015–2017	Station redevelopments and electrification upgrades to existing rail network.
2019	Full service operation of Crossrail from Reading to Abbey Wood and Shenfield.

3. Empirical strategy

Our approach to evaluate the WTP for better access to stations scheduled for Crossrail upgrade relies on hedonic modelling (Rosen, 1974). This technique allows to express the price of a complex good as a function of multiple intrinsic and extrinsic characteristics of a property (Dubé et al., 2014): *structural attributes* such as bedrooms, bathrooms, or gross floor area; *locational* attributes like accessibility to a range of amenities; and *environmental* attributes relating to factors like atmospheric pollutants. Hedonic approaches model the recovery of the implicit price as valued by home-buyers for their utility-bearing characteristics (Lancaster, 1966; Mathur and Ferrell, 2013).

Practically speaking, this approach translates into a regression on which the (log of the) property price is explained as a function of the different characteristics. Because our focus is on the effect of the Crossrail intervention, we will include several characteristics usually employed in this framework, but pay particular attention to the findings

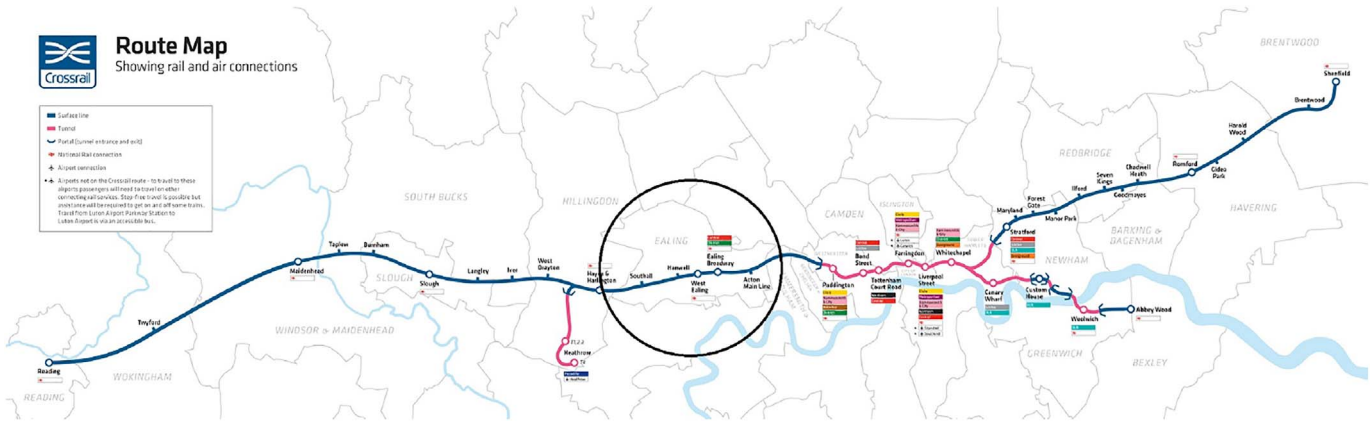

Fig. 1. Crossrail route map (Crossrail, 2014). Service provision for Ealing is planned to be provided by Southall, Hanwell, West Ealing, Ealing Broadway and Acton Main Line stations (encircled) (Crossrail, 2016e).

of the distance to the Crossrail stations. We begin our empirical exercise with a baseline regression that is very simple conceptually but involves many assumptions, some of which we will relax on subsequent models. Our initial specification is as follows:

$$\log P_i = \alpha + dist_{CRi}\ \beta_1 + X_i\ \beta_k + \varepsilon_i \tag{1}$$

where the price P_i is transformed in logarithms to allow us to make percentual interpretations; all the control variables for property i in Table 2 are collapsed into X_{it}; β_k is a vector or parameter estimates for each of the variables in X_{it}; ε_{it} is an error term assumed to be i.i.d.; and β_1 is the parameter of interest for $dist_{CR}$ that captures the effect of the distance from property i to the nearest station scheduled for Crossrail upgrades.

Our initial equation contains two main assumptions that make challenging to claim β_1 is an accurate estimate of the effect of the Crossrail announcement: spatial randomness and the persistence of confounding factors. The inherent spatial nature of the data means that values are likely to be spatially correlated. The proportion of unexplained variance in price determination may relate to a spatial component (Anselin and Lozano-Gracia, 2008). If the data generating process contains spatial autocorrelation, this may produce biases in the estimated variance used for statistical inference. To account for this possibility, we estimate a second equation that improves the baseline by modelling spatial effects of unobserved characteristics:

$$\log P_i = \alpha + dist_{CR}\beta_{1-sp} + X_i\beta_{k-sp} + u_i \tag{2}$$

where everything applies as in Eq. (1), except that we relax the assumption that the error term is well-behaved. Instead, we allow for the possibility of spatial autocorrelation in the form of an autoregressive term:

$$u_i = \lambda \sum_j w_{ij} u_j + \varepsilon_i \tag{3}$$

where w_{ij} is the ij-th cell of a spatial weights matrix W. A fundamental element of spatial econometrics (Anselin, 1988), W is an $N \times N$ positive matrix that captures the spatial arrangement of the properties by assigning non-zero weight to pairs of observations assumed to be spatial neighbours, and zero otherwise. Given the nature of this application and of the spatial characteristics of the data points, we define neighbours following the k-nearest neighbour criterion by which every observation i is assigned as neighbours its k nearest observations. Our spatial weights are specified as k-nearest neighbours given the varying density of the housing transaction point pattern over space. In the present study, the bandwidth of the distance threshold causes properties in dense areas to have a disproportionate number of neighbours relative to properties in sparser areas; this is undesirable as it increases the variance of the spatial lag. We show results only for $k = 15$, although we tested the sensitivity of results to different configurations of k and W, obtaining virtually the same results. Once constructed, we row-standardize the matrix so that $\sum_j w_{ij} = 1$, effectively capturing the average value for the error term in the neighbourhood of i. Finally, the

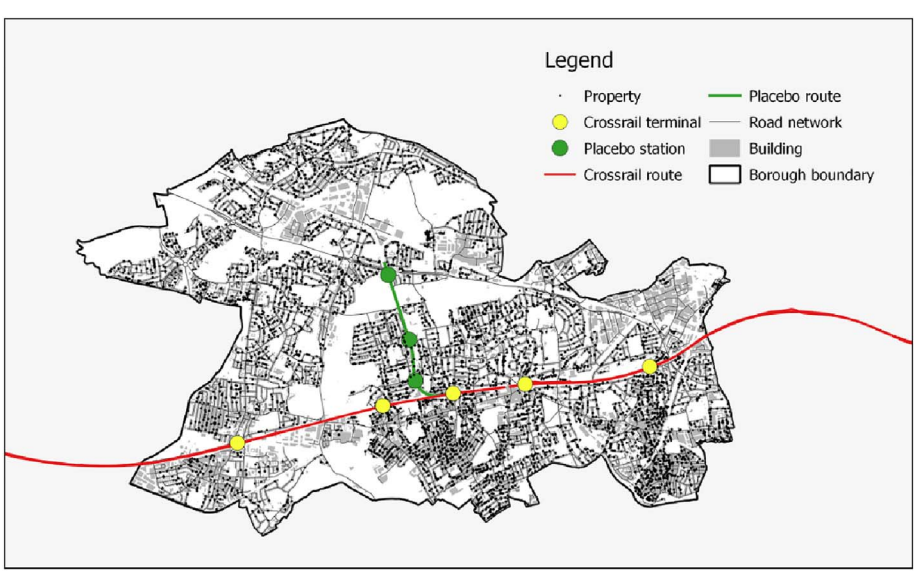

Fig. 2. Ealing's Crossrail corridor, spatial distribution and placebo test.

Table 2
Summary of continuous and dummy variables.

Variable	Description	Source	Mean	Std. dev	Unit
P	Transaction price of property.	Land Registry.	322,217	233,707	Pounds
TERRACE	1 if terraced housing, 0 otherwise.	Land Registry.	0.25	0.43	Binary
DETACHED	1 if detached housing, 0 otherwise.	Land Registry.	0.02	0.15	Binary
FLAT	1 if flat/maisonette housing, 0 otherwise.	Land Registry.	0.45	0.50	Binary
TENANCY	1 if freehold, 0 otherwise.	Land Registry.	0.53	0.50	Binary
AGE	1 if new build property, 0 otherwise.	Land Registry.	0.44	0.50	Binary
CBD	Straight-line distance to CBD.	EDINA Digimap.	13.38	2.91	Kilometre
NR	Nearest National Rail overground station.	EDINA Digimap.	0.96	0.58	Kilometre
UG	Nearest London Underground subway station.	EDINA Digimap.	1.30	1.00	Kilometre
AIRPORT	Distance to London Heathrow Airport.	EDINA Digimap.	9.33	3.74	Kilometre
Post	1 if post-announcement, 0 otherwise.	Own calculations.	0.38	0.49	Binary
distCR	Nearest planned Crossrail station.	Crossrail.	1.78	1.27	Kilometre
INCOME	Median gross income by Output Area.	GLA Intelligence.	47.59	13.91	000s
POP	Population density by LSOA.	ONS.	27.39	17.71	Square Kilometre
GREENSPACE	Nearest green space amenity.	EDINA Digimap.	0.26	0.17	Kilometre

parameter λ, ranging from −1 to 1, captures the extent to which spatial autocorrelation is present in unobserved variables relevant to the model.

Even when controlling for spatial autocorrelation, confounding variables may remain latent in cross-sectional models. For this reason, we expand our initial approach to include an alternative identification strategy used in econometrics for programme evaluations: the difference-in-difference (DiD) estimator. DiD estimates the impact of a treatment on a given outcome over a sample that includes both treated and non-treated observations, as well as observations recorded before and after the treatment under the assumption that treatment states have similar trends to control states in absence of the treatment. In a nutshell, DiD estimators provide a spatio-temporal framework that eliminates the influence of all constant observable and unobservable non-random differences influencing the price determination process (Hijzen et al., 2013) by mimicking quasi-experimental designs.

Typically, DiD hedonic housing models compare the difference in average housing prices before and after a critical date by establishing two counter factual states for each agent in the population: a treatment group of properties "affected" by the intervention and a control group of properties that do not experience any change (Angrist and Pischke, 2008; Dubé et al., 2014). This involves differencing the average gain in the control group from the average gain in the treatment group. In econometric terms, this removes biases in the post-treatment comparison that could emanate from the permanent differences and temporal trends between the treatment and control groups in the first place. Standard DiD designs code observations *i* for two time periods *t*– before and after the treatment – and further split them by $D \in \{0,1\}$, where 0 $D_i = 1$ represents *i* having been treated (Delgado and Florax, 2015).

In the context of our study, the policy intervention is taken to be the 2008 official announcement of Crossrail which constitutes the pre- and post-announcement binary split.[3] Additionally, instead of opting for a binary split for treated and control groups, we use instead a "continuous treatment": the distance of a given property to the closest station scheduled for upgrade. By this method we imagine a continuum of counter factual states. Therefore, we identify the causal effect of announcing Crossrail as the interaction of the post-treatment dummy (*Post*) and the continuous distance to the station ($dist_{CR}$). Ignoring for now the spatial autocorrelation issue, the specification is as follows:

$$\log P_{it} = \alpha + dist_{CR}\beta_{1-did} + \beta_{2-did}Post + \beta_{3-did}dist_{CR} \times Post + X_{it}\beta_{k-did} + \varepsilon_{it} \quad (4)$$

where the notation holds as in Eq. (1), but is expanded to include the interaction between $dist_{CR}\beta_{1-did}$ and $\beta_{2-did}Post$ for $\beta_{3-did}dist_{CR} \times Post$. This approach calculates the marginal change in a post-announcement property value resulting from a unit increase in treatment intensity (km to the targeted station). In other words, β_{3-did} captures whether properties nearer to proposed Crossrail terminals experienced a premium in property value post-announcement. Consequently, a positive and significant estimate would point to a positive valuation by home-buyers of the Crossrail project.

These two approaches can be combined, giving rise to the most robust specification, which we will take as the preferred one:

$$\log P_{it} = \alpha + dist_{CR}\beta_{1-sdid} + \beta_{2-sdid}Post + \beta_{3-sdid}dist_{CR} \times Post + X_{it}\beta_{k-sdid} + v_{it} \quad (5)$$

which is virtually the same as Eq. (4), but incorporating a spatial error term v_{it}:

$$v_{it} = \lambda \sum_j w_{ij-t} v_{jt} + \varepsilon_{it} \quad (6)$$

which also has a very similar structure to the error term in Eq. (3), but crucially differs in that observations are allowed to be spatial neighbours, and hence have a non-zero w_{ij} weight, only if they were both sold in the same period *t*. Similarly to its cross-sectional equivalent, we use a *k*-nn approach to define spatial relationships, and present results for $k = 15$, although the model proved robust to alternative specifications.

Although we will take β_{3-sdid} as our preferred estimate, we take a further step in exploring the dynamics of the anticipation process. To do that, we disaggregate the two time periods (before/after) into more fine grained quarters, which we interact with $dist_{CR}$ for those belonging to the post-announcement period:

$$\log P_{it} = \alpha + dist_{CR}\beta_{1-tdid} + \gamma_Q + \sum_{PQ} \beta_{PQ-tdid} dist_{CR} \times \gamma_Q + X_{it}\beta_{k-tdid} + \varepsilon_{it} \quad (7)$$

where γ_Q are quarter fixed effects (disaggregating the overall β_2), and $\beta_{PQ-tdid}$ are parameters that capture the premium attributable to each post-announcement quarter, which disaggregates the effect of β_3 over quarters. Crucially, the summation $\sum_{PQ}$ creates an interaction between treatment intensity (distance) for each quarterly dummy variable post-treatment.

4. Results

4.1. Main results

Our point of departure is the baseline OLS model. Of the structural control variables that enter Eq. (1), detached housing units commanded 51% premiums over terraced housing and flats with properties sold as

[3] Our 6 year interval is rationalised by findings in McMillen and McDonald (2004) which demonstrate housing markets react to transport policies 6 years after announcement.

freehold eliciting premiums of 41.0%. Yet, somewhat counter-intuitively, housing sold as new build depreciated property by −19%.

As for the locational variables that enter the house price determination process, affluent neighbourhoods with higher median household incomes (expressed in £10,000) is significantly correlated with house prices, with a positive coefficient of 1.5. Moreover, increasing population density by one-unit (i.e. 100,000 people per square kilometre) was significantly associated with a property devaluation of 0.1%. Distance-to-CBD was a significant determinant of property value with 3.2% premiums observed per kilometre reduction from employment centres in the City of London – possibly reflecting the centralisation of jobs in the CBD.

The estimates of environmental variables computed coefficients consistent with conventional wisdom: open space amenities as value-enhancing land uses carry significant 7% premiums per kilometre reduction from open spaces. Next, we observe significant price discounts of 2.8% for every kilometre a house is closer to London Heathrow Airport, most likely reflecting the disamenity of noise and visual disturbances associated with aviation activity.

For rail access, the capitalisation of journey-time savings provided by London Underground stations carries a significant price reduction of 0.6% per kilometre reduction in station-distance. On the other hand, proximity to National Rail stations is an insignificant determinant of property value which may reflect the negative externalities of subway systems. Bowes and Ihlanfeldt (2001), for example, explain the attractiveness of neighbourhoods to criminals is dependent on the potential booty, measured by density of retail employment, population density and median neighbourhood income. For these reasons, perhaps the disamenity of a potential for higher crime rates surrounding National Rail stations discounts the utility of transport access. This finding is implicit of potential spatially non-linear effects which reflect both positive and negative amenity impacts of rail stations.[4]

Finally, the naive OLS estimate of the baseline model shows the preference of home-buyers for locations nearer to planned Crossrail stations is reflected by an increase of ≈4% in property value per kilometre decrease from future Crossrail terminals. This result would suggest Crossrail's anticipated journey-time savings caused property valuations to increase for Ealing's property market.

To test the robustness of these empirical findings to potential spatially correlated omitted variables that area function of transacted property values, column (2) of Table 3 introduces the spatial cross-sectional model[5] described in Eq. (3). When incorporating a spatial dimension to model estimation, we find comparable signs and coefficient estimates to the baseline model. Overall, our finding of interest notes a marginally higher premium of 6% per kilometre increase to locations scheduled for Crossrail upgrades. Although marginally higher, given the effect size remains in the same ballpark as our OLS estimate, we can be reasonably reassured of inference. Yet, do we observe deflation to the magnitude from 0.006 → − 0.01 of the London Underground variable when taking account spatial structure in the error covariance matrix. Whilst the main objective of this econometric model is to obtain efficient and unbiased parameter estimates, Eq. (3) omits the temporal dimension which we address below.

In building on the cross-sectional models, column (3) of Table 3 shows OLS estimates of the DiD model defined in Eq. (4). The immediate picture from this specification is that the DiD findings are comparable in the signs and magnitudes of estimates to the cross-sectional models. Turning to the DiD parameters, we note several findings. Despite the continuous nature of the treatment variable, Crossrail, the formulation retains features of a generalised DiD model. Consistent with our baseline OLS, the Crossrail parameter estimated a 4% increase in housing prices per kilometre decrease from scheduled Crossrail terminals. Our coefficient for Time reflects the pure passage in time absent from the interaction with the actual intervention. The parameter estimate implies a 26% change in the expected mean of logged housing prices from before to after the announcement of the Crossrail intervention. The main finding from the DiD model supports our research hypotheses of an anticipation (causal) effect of the Crossrail intervention on housing prices. We find, even when controlling for overall trends affecting both treated and non-treated observations, for every kilometre a house is closer to stations scheduled for Crossrail upgrades, home-buyers are willing to pay an extra 2.5% after the announcement of the upgrades, suggesting a positive and significant anticipation effect.

In order to account for potential remaining spatial autocorrelation, we further estimate the spatial DiD (SDiD) specification in Eq. (5). Overall, the total effects of the SDiD are comparable to the DiD with consistent signs and effect sizes for both models.[6] Column (4) of Table 3 shows the results for the SDiD model, finding identical 2.4% premiums per kilometre increase to Crossrail stations. Yet, the dissimilarity between the DiD and SDiD estimators lies in the inclusion of lambda. In the present study, the high significance and magnitude of lambda is indicative of spatial autocorrelation present in unobserved variables relevant to the SDiD model. This supports the superiority of the SDiD in correcting for biases in the DiD estimator. In building a model robust to spatial and temporal dimensions, we infer that properties situated nearer to planned Crossrail stations, relative to those of properties distant, changed significantly following post-announcement compared to their pre-announcement trend.

4.2. Sensitivity and robustness

In this section, we expand our results further in two main directions: first, we consider a finer time disaggregation; and second, we test the validity of our core findings by carrying out a placebo experiment. To obtain higher granularity in the estimates of anticipation effects, we interact 47 quarterly dummies – from quarter 2 of 2002 to quarter 4 of 2014 – with the *Crossrail* treatment. Given the large number of coefficients, we use a graphical representation of the relevant part of the model output, rather than a tabular display. Fig. 3 depicts the estimates in absolute values of these interaction terms together with their 95% confidence intervals and shows the evolution of the premium placed on locations nearby the stations announced to be upgraded. These findings suggest a change in trend post-announcement (vertical red line).

From this we can derive that even just measuring anticipation, with data imperfections and limitations, the graph clearly shows a change in trend some time after the 2008 announcement. A possible explanation is that housing markets may be sluggish to price adjustments caused by the announcement of network improvements if the following provisos are not met: that home-buyers are perfectly informed, perfectly rational and face no credit constraint (Grimes and Young, 2013). These circumstances may arise when there exists a time lag between the reactions of home-buyers to the dissemination of Crossrail's transport improvements by media outlets.

To further corroborate the validity of our DiD estimator, we run a placebo experiment. The basic idea is to show that the effect we are able to recover in our DiD estimations responds to the treatment that affects exclusively to the stations targeted for Crossrail upgrade and not to other ones. To do that, we create a “fake treatment” that affects the National Rail stations along the North-South corridor, almost

[4] To test this, we introduce a quadratic polynomial to the London Underground and National Rail variables, finding the coefficients become significant. Yet, given the estimate for the coefficient of interest does not change, we omit higher order polynomials from our model specification.

[5] For robustness, we test the sensitivity of Eq. (3) to maximum likelihood estimation (MLE) and instrumental variable (IV) estimation finding comparable estimates across both models.

[6] Sensitivity of the SDiD to distance band weights is tested, obtaining virtually the same results as the *k*-nearest neighbour weights.

Table 3
Estimation results.

	(OLS)	(Spatial OLS)	(DiD)	(Spatial DiD)	(Placebo)
Constant	12.14***	12.19***	12.19***	12.17***	12.25***
	(0.020)	(0.036)	(0.019)	(0.019)	(0.017)
Age	−0.19***	−0.06***	−0.17***	−0.17***	−0.17***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)
Airport	0.028***	0.03***	0.02***	0.02***	0.02***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
CBD	−0.032***	−0.04***	−0.04***	−0.04***	−0.05***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.000)
Crossrail	−0.04***	−0.06***	−0.03***	−0.03***	
	(0.002)	(0.005))	(0.002)	(0.002)	
Detached	0.51***	0.42***	0.49***	0.49***	0.50***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.010)
Flat	−0.13***	−0.11***	−0.13***	−0.13***	−0.13***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)
Greenspace	−0.07***	−0.09***	−0.07***	−0.07***	−0.10***
	(0.009)	(0.023)	(0.008)	(0.008)	(0.009)
Income	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
National Rail	−0.003	0.01	−0.01***	−0.01 **	−0.02***
	(0.003)	(0.007)	(0.002)	(0.002)	(0.003)
Pop den.	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Crossrail*Time			−0.025***	−0.024***	
			(0.002)	(0.002)	
Tenancy	0.41***	0.47***	0.41***	0.41***	0.41***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Terrace	−0.07***	−0.02***	−0.08***	−0.08***	−0.08***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Time			0.26***	0.26***	0.23***
			(0.005)	(0.005)	(0.005)
Underground	0.006**	−0.01*	0.003	0.004	0.04***
	(0.003)	(0.007)	(0.003)	(0.003)	(0.002)
Lambda		0.67***		0.12***	
		(0.006)		(0.011)	
Placebo*Time					−0.01
					(0.002)
Observations	50,863	50,863	50,863	50,863	50,863
Adj-R^2	0.6167	0.6578	0.6582	0.6582	0.6547

Note: pseudo R^2 given for columns (2) and (4).

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

orthogonally to those truly affected (see Fig. 2). In column (5) of Table 3, we re-estimate the DiD specification using distance to the closest station "fakely treated". This builds the robustness of our empirical findings to distance-to-CBD trends in housing prices. As the estimate shows, the interaction between the placebo and time dummy variable is statistically insignificant and close to zero. This result reinforces our conclusions about the causal effect of Crossrail stations.[7]

5. Discussion and policy implications

Generally, the outcomes of this paper *somewhat* coincide with those found in other instances of the literature: housing markets positively react to rail interventions, potentially as early as short after a project is announced. Yet, relative to the impacts of rail access in property markets elsewhere, there is a dissimilarity between premiums estimated in Ealing to those estimated by previous studies that investigate causality between rail station proximity and property value (see Table 4). McMillen and McDonald (2004), for example, observed 19.4% premiums per 1.6 km decrease from rail interventions in suburban Chicago. Likewise, Debrezion et al. (2011) identified 32.3% premiums for housing near rail stations in the Amsterdam, Rotterdam and Enschede regions of the Netherlands. Most alarmingly, (Mohammad et al., 2013) meta-regression study found 8.7% premiums for residential properties situated between 501–805 m from commuter rail systems. Putting this into perspective, the naive estimates of this study found only 4% premiums per kilometre decrease from Crossrail stations.

In principle, the lower pricing effect observed could be attributed to the pre-existing high level of transport accessibility in London's metropolitan area. For Hamburg – a city similar in regards to the multimodal transport environment of London – Brandt and Maennig (2012) observed lower premiums of 4.6% for condominiums situated within 250–750 m of commuter rail stations. Similarly, Gibbons and Machin (2005) found 1.5% to 4.0% premiums per kilometre reduction to rail interventions in Bromley, London. These two findings shown in bold in Table 4 are far more aligned with estimates obtained by this study, which may be attributed to a number of explanations addressed below.

[7] Although not reported here, we have also checked the influence of potential multicollinearity that some of the regression diagnostics highlighted. To do that, we ran a small Monte Carlo simulation that randomly removes a small number of observations and reruns the regression, keeping the parameter estimate. If multi-collinearity was indeed a problem, these values might jump around and display a large variance. Instead, what we obtain is a nicely behaved normal curve centred around our original estimate and with a very small variance, strongly suggesting multi-collinearity does not impose any challenge to our conclusions. Results available upon request.

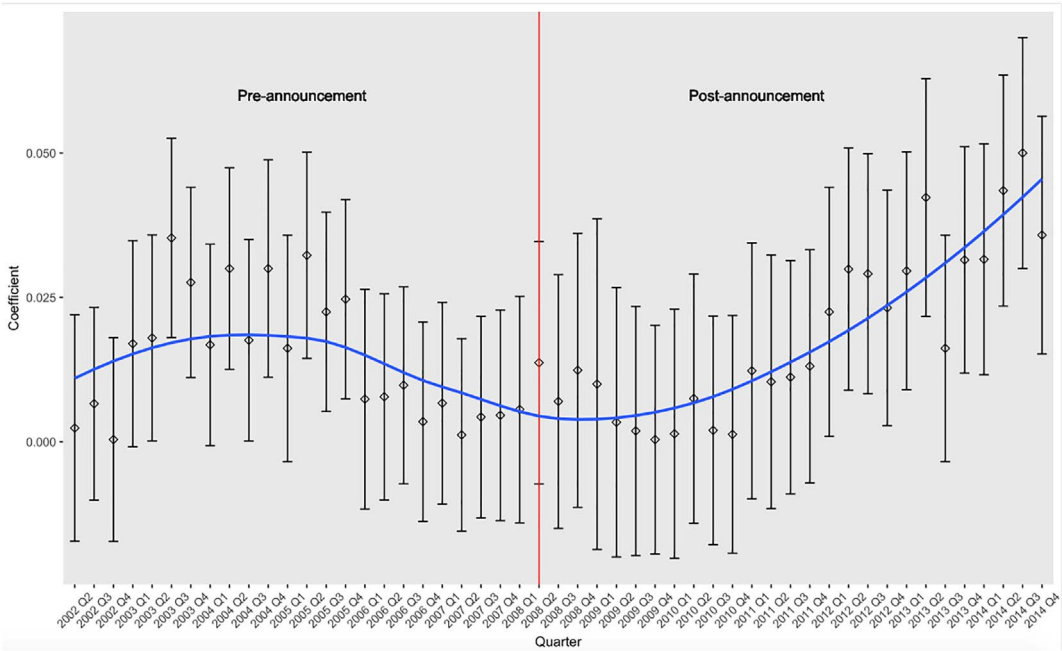

Fig. 3. Quarterly growth of anticipation effect. *Note*: Dots represent the quarterly point estimates as absolute values, vertical bars show the 95% confidence intervals, and the blue line indicates the loess line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Previous findings in the hedonic literature for rail interventions.

Author	Study area	Positive effect
McMillen and McDonald (2004)	Chicago, US	19% per 1.6 km reduction from station
Debrezion et al. (2011)	The Netherlands	2.4% per 250 m reduction from station
Grimes and Young (2013)	Auckland, New Zealand	5–7.9% (≤2 km)
Efthymiou and Antoniou (2013a)	Athens, Greece	9.2% (≤500 m)
–	–	–
Mohammad et al. (2013)	Meta-regression	8.7% (501–801 m)
Brandt and Maennig (2012)	Hamburg, Germany	**4.6**% (≤1 km)
Gibbons and Machin (2005)	London, UK	**1.5–4.0**% per 1 km reduction from station

One important factor accounting for differences in the between-study estimates for rail access are the circumstances of the study area. Before generalising, it is imperative to recognise findings as a function of the local characteristics of the study region – supply-demand dynamics of the housing market, macroeconomic conditions or existing transport substitutability.

Despite this, differences may still link to methodological considerations in the models estimated by studies in the literature. By employing a quasi-experimental design using DiD estimators, we adopt a more robust identification strategy. In support of Dubé et al. (2014), an important contribution of this study finds that the estimation of housing premiums in naive OLS models differs from those employing a spatial autoregressive specification in the hedonic price equation. We find a motivation in specifying a SDiD estimator shown by the magnitude and significance of the autoregressive coefficient (which signifies a spatial structure in the data). From this, we infer that failing to construct more robust econometric models may lead to a biased statistical inference of housing premiums.

One might point to the fact the premiums obtained for the DiD are only 0.1% higher than those for the SDiD estimator. Yet, once transposed to GBP(£), and the premium is traversed across Ealing's total stock values, the monetary impact becomes more pronounced. For example, if we take the average price of a property ≥1 km from Crossrail stations as £397,200 post-treatment, the DiD estimate 2.5% premium per kilometre decrease from planned Crossrail stations would mean a property would grow by £9930 had the property been situated a kilometre closer. Under the same scenario, the SDiD estimate of 2.4% can be monetised as £9532. In all, although this reflects a marginal difference between both estimators, the example is pertinent to how it can represent a large monetary effect if traversed across all properties sold in Ealing, which is particularly important if such models are used to inform policy evaluations.

A further reason why the coefficients estimated by this paper are lower than those identified by the literature may link to the fact that other studies evaluate pre-existing transport interventions – a novelty of this study is that we look at the anticipatory effects linked to proposed infrastructural improvements. Anticipation effects arise in speculation of proposed transport outcomes, and may accrue in housing markets if home-buyers or developers speculate on the sale of land in expectation of location premiums once the intervention has been constructed (Heckert and Mennis, 2012). The outcomes of this study confirm this, and support evidence from Grimes and Young (2013) and McDonald and Osuji (1995) that the anticipated benefits of transport improvements are factored into home-buyer's location and pricing decisions following their announcement.

On the dimension of time, Efthymiou and Antoniou (2015) further stress the direct and indirect effects of time on the relationship between transport location and real estate prices. By building on previous research (Efthymiou and Antoniou, 2013b), they demonstrate a decrease in the willingness-to-pay for proximity (< 500 m) on purchasing prices decreased by 42.5% for dwellings in Athens during the ongoing financial crisis between 2011 and 2013. Clearly, the time of analysis accounts for the impact variation of transport infrastructure, with the sensitivity of housing prices to macroeconomic conditions a strong determinant of the willingness-to-pay for location premiums. Given the time-line of the present study coincided to a deterioration of the UK's housing market conditions, it is possible that usually strong determinants of housing prices such as transport interventions lose their impact which may account for the lower bounds of our estimates. For this to be the case, however, it would have to be an effect of the crisis that only

affected properties closer to upgraded stations, as otherwise the DiD method would abstracts this unobserved heterogeneity.

Yet, for Ealing, it is possible the model's we employ may underestimate the final total effect of the Crossrail intervention. As Ealing is dominantly an owner-occupied property market (Ealing Council, 2011), anticipation effects linked to Crossrail's announcement may increase given longer time horizons. This is because owner-occupiers have been found to have shorter-run views of the anticipatory effects of policy interventions[8] (McDonald and Osuji, 1995). Under this intuition, if home-buyers who plan to become owner-occupiers are less receptive to the anticipated effects of future rail interventions, there may be less of an incentive to purchase property in investment areas because "they must commute from day one" – i.e. prior to the opening of the transport innovation anyway (Gibbons and Machin, 2005).

Therefore, the premiums linked to the anticipation of policy interventions may rise in housing markets with a higher ratio of landlords. For Ealing, 28% of the total 124,082 properties are privately rented with 53% owner-occupied (Ealing Council, 2011). With this market share reflecting a dominance of owner-occupied home-buyers, it is expected that price adjustment is more likely to occur nearer to the time of Crossrail's opening. In this way, as this study's data differences property sales between 2002 and 2014, it is probable our model's estimated premiums underestimate the transport benefits than if property sales were pooled for years closed to Crossrail's completion in 2019. Therefore, whilst the anticipated benefits of Crossrail *was found* to have been speculatively internalised into the home-buyer's WTP, the magnitude of these premiums may have been relaxed by sluggish price adjustment to the anticipation of new rail services.

6. Conclusion

Rail transit is a key determinant of land use evolution (Efthymiou and Antoniou, 2013a). Property markets are conduits for the economic impact of transport interventions and so provide a compelling backdrop reflecting these changes. In this paper, we estimate how home-buyers anticipate the benefits of a rail upgrade intervention by considering the area of Ealing in London and the announcement of Crossrail in July 2008.

As the Crossrail innovation remains under construction, the intervention we consider is the announcement of the project, rather than its completion. To obtain the most possible accurate estimate of its causal effect on house prices, we use a combination of DiD estimation and spatial econometrics whilst introducing further robustness checks. This approach allows us to isolate the effect of exogenous changes in transport accessibility whilst controlling for spatial effects of property sales and the temporal dimension of the data. In doing so, we explore the anticipatory effect attributed to the implied journey-time savings by estimating the value of service-level improvements to home-buyers who live, or intend to live, in Ealing. Controlling for unobserved spatial effects, our DiD models find for every kilometre a house is closer to a station scheduled for Crossrail upgrades, home-buyers are willing to pay between 2.4% and 2.5% extra, down from the 4% premium estimated by the naive OLS estimator. In support of Gibbons and Machin (2005), we take this as evidence that cross-sectional models overstate the premiums for transport access even when saturated with control variables.

Relative to past research, the low magnitude of the coefficient may be linked to two considerations: (1) sluggish price adjustment to the anticipation of the new lines opening; and (2) the intervention was constructed in an area of high transport substitutability – i.e. multiple alternative transportation modes (Liu et al., 2009). Irrespective of this, we find the announcement of Crossrail was positively capitalised into Ealing's housing market, with a higher WTP for properties nearer to stations expecting the Crossrail treatment. This would appear to align with Crossrail's objective to increase residential capital values and impact property investment decisions in London's housing market (Crossrail, 2016c). Future research might seek to confirm our findings by applying the same quasi-experimental methodology, but by pooling property sales data some time after Crossrail has been completed (post-2019).

[8] By contrast, an asset-based view prevails in property markets dominated by private landlords because absentee landlords derive revenue streams from charging rentals.

Acknowledgments

We would like to thank and acknowledge participants at the Special Cluster 8 Workshop: Big Data: a new opportunity for urban transport and mobility policies held on 10–11 March 2016 in Seville, Spain for constructive comments.

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