Mind the Gap: Windfall Gains in Housing Values Along London's Elizabeth Line

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Abstract

This dissertation measures the impact of the Elizabeth line on residential property values. Using a difference-in-differences model on 18 years of transaction data within 3 kilometres of all 41 stations, average price uplifts of 3.15%, 5.31% and 3.01% are identified during the line's announcement, construction and post-opening phases respectively. Properties closest to stations and those near major interchanges experience substantially larger effects. Results are consistent across models and satisfy the parallel trends assumption. With an estimated aggregate windfall gain of £3.08 billion — equivalent to 16.3% of total construction costs — the findings support greater use of land value capture mechanisms to help fund future infrastructure investments.

Contents

1 Introduction

Cities remain a pillar of economies. Home to 56% of the world's population and generating over 80% of global GDP, urbanisation can be a key driver of individual and national development (World Bank, 2023). This is especially true in the UK, where cities account for 9% of land, but outputs 63% of GVA (Centre for Cities, 2025). Transport infrastructure is vital and a necessary condition for the continuous operation of urban life, particularly in response to population growth. Beyond reducing travel times for its own and competing users, public transport helps boost total factor productivity (Anas & Chang, 2023), relieve congestion (Anderson, 2013), reduce car-related accidents and injuries (Bauernschuster et al., 2017), enhance health outcomes (Sener et al., 2016) and improve air quality at certain sites (Ma et al., 2021). The well-established socioeconomic and environmental benefits present clear grounds for public investment into improving inter- and intra-city connectivity; however, limited public funds naturally constrains the number of transport projects ultimately executed.

A widely-studied outcome of transport infrastructure expansion is an increase in property values near the stations, a phenomenon referred to as land value uplift (LVU). The existence of positive capitalisation effects from rail transit systems is very well documented in research covering many cities worldwide in the past five decades. Since 1970, there have been over 200 studies exploring transit-induced LVU (Rennert, 2022), with over 60 studies conducted in North America alone (Higgins & Kanaroglou, 2016). This has important implications on capturing these gains to finance ongoing or future projects via land value capture (LVC).

One of the most notable examples of transport infrastructure expansion in recent years is the construction of the Elizabeth line, a major public transport project aimed at improving connectivity and reducing travel times across London and its neighbours, as well as reducing regional inequality.

Applying a difference-in-differences framework highlights that the Elizabeth line has resulted in positive capitalisation effects on housing values. Across the entire study boundary, at the announcement phase, prices on average rose by 3.15%, 5.31% during the construction phase and 3.01% after opening. Further models reveal that properties within 0–900 metres of stations experience even stronger uplift, particularly if the station has at least two connecting lines. This may explain why capitalisation effects are more prominent in Central London. The results satisfy the parallel trends assumption, and are robust to reweighting on observed characteristics and clustered standard errors.

These findings imply total LVU of £3.08 billion, or 16.3% of construction costs, suggesting that LVC mechanisms on residential properties, similar to the Business Rate Supplement applied to commercial properties, would aid in funding essential transport infrastructure. Such a move would shift London closer to the beneficiary pays principle used by Hong Kong, Singapore and other jurisdictions.

The paper is organised as follows. Section 2 reviews the related literature surrounding rail transport infrastructure expansion on residential property values. Section 3 provides a brief history and overview of the Elizabeth line. Section 4 describes the data and section 5 details the empirical methodology. Section 6 presents the results. Section 7 performs several robustness checks. Section 8 discusses the results and the policy implications. Section 9 concludes.

2 Literature Review

2.1 Transport Network Expansion and Land Value Uplift

Bid-rent theory connects the expansion of transportation infrastructure to LVU. Building upon Von Thünen's (1826/1966) early work on farmland values and accessibility, Alonso (1964), Muth (1969) and Mills (1972) extended this idea to urban land markets in the monocentric city model. Under this framework, the spatial distribution of firms and households in a city is explained by the trade-off between land use and commuting costs, illustrated by the negative relationship between land prices and distance from the central business district known as bid-rent curves. This creates a utility maximisation problem whereby firms and households locate at a distance that balances travel costs and land rents based on their preferences. Since the physical characteristics of land are assumed given, this theory posits that location is the primary factor determining land values. As transport infrastructure reduces commuting costs, in terms of both time and money, improved accessibility should lead to increased bidding between users for properties close to stations, resulting in LVU and a localised, negatively sloped bid-rent curve away from stations.

The majority of studies have found positive capitalisation effects (Mohammad et al., 2013; Rennert, 2022). Contemporaneously, negative capitalisation effects (Landis et al., 1995; Nelson, 1992; Wagner et al., 2017) and insignificant results (Clower & Weinstein, 2002; Du & Mulley, 2007; Gatzlaff & Smith, 1993) have also been identified in a few cases. Furthermore, many authors find that capitalisation effects materialise long before the official opening of the line (Damm et al., 1980; McDonald & Osuji, 1995; McMillen & McDonald, 2004; Yen et al., 2018).

The first major meta-analysis, by Debrezion et al. (2007), attempted to explain some of this heterogeneity in the magnitude and sign of results, and concluded that LVU is stronger for commercial property for short distances from stations, but accessibility premiums persist across longer distances for residential property. In addition, commuter rail transit stations produce stronger uplift than stations pertaining to other transport modes, and highway accessibility diminishes transit-induced LVU due to its competing nature. Mohammad et al. (2013) build upon this foundation by incorporating more contextual and methodological factors, and extend the geographical scope beyond North America by including studies in Europe and Asia. Their results confirm the key findings by Debrezion et al., and indicate stronger LVU effects in Europe and East Asia compared to North America, possibly due to greater reliance on public transit systems in these regions. Most recently, Rennert (2022) separates these two factors by controlling for public transport expenditure share, concluding that more expensive transit services, relative to income, reduce accessibility benefits, larger transit networks generate marginally higher effects, and that results from Europe, Asia and Oceania are statistically similar to North America, whereas East Asia produces lower results.

Furthermore, Bowes and Ihlanfeldt (2001) theorise that LVU could be the effect of positive benefits such as accessibility and retail development net of negative externalities and crime, particularly for properties situated closest to stations. Capitalisation effects may also be dependent on the project's success; for example, the study by Wagner et al. (2017) was distinct in that the LRT system examined was among the worst performing LRT lines in the US at the time in terms of ridership, profitability and relative accessibility benefits, which contextualises the land value depreciation of 7.8%. Economic decline within the study area may further contribute to insignificant or low capitalisation effects (Du & Mulley, 2007; Gatzlaff & Smith, 1993; Hess & Almeida, 2007). Beyond area-specific variations in effects, a few studies have discovered network effects of various forms — whether through increased connectivity at a former terminus station gaining integration (Higgins, 2019), enhanced accessibility benefits extending beyond immediate catchment areas (He, 2020) or uplift along the existing line, especially at interchange stations (Zhu & Diao, 2024).

2.2 Hedonic Analysis

Hedonic pricing theory, originating from the seminal work of Rosen (1974), has long been a popular method in the applied economics literature due to its wide applicability. By incorporating housing and locational controls along with a distance variable, researchers can estimate LVU using cross-sectional or before-and-after ordinary least squares (OLS) regressions. However, because unobserved factors may simultaneously influence both property values and accessibility, OLS can introduce endogeneity. An example of omitted variable bias in early studies involves the omission of competing accessibility factors, such as distance to highways, which leads to an overestimation of proximity effects (Debrezion et al., 2007; Mohammad et al., 2013). The omission of local crime statistics among other neighbourhood amenities could also bias estimates (Bowes & Ihlanfeldt, 2001).

Repeat-sales models are used to control for endogeneity by removing biases caused by time-invariant omitted variables. Although this approach requires lower-resolution data, it introduces further problems. Not only is the sample size drastically reduced in the process, but there may also be sample selection biases if houses that are sold at least two times are materially different from those that sell just once (Gatzlaff & Haurin, 1997). Moreover, many housing and neighbourhood characteristics do change over time, even if slowly; therefore, differencing housing prices relies on a flawed assumption of time-invariant attributes that may not adequately address endogeneity.

2.3 Difference in Differences

Difference-in-differences (DID) studies have become increasingly adopted in the transit-induced LVU literature. The essence of DID lies in combining the strengths of before-and-after and with-and-without analyses by testing the pre- and post-intervention changes between treated and control groups following an exogenous shock, whilst controlling for observed and unobserved confounders. Using DID in lieu of a standard OLS regression mitigates concerns of endogeneity, but in turn introduces the crucial new assumption of parallel trends.[1] The ability to establish causality makes DID a powerful tool for impact evaluation, and like OLS, DID's versatility makes it a popular methodology for many fields beyond economics.

Gibbons and Machin (2005) followed the DID method to estimate the effect of new Docklands Light Railway (DLR) and Jubilee line stations on property values. Using data from Nationwide Building Society, the authors restrict their sample to properties within 30 kilometres from Holborn (a proxy for London's central business district), and find that a 1km reduction in distance to the nearest Jubilee line or DLR station increases property values by around 2.1% for properties within 2km of a station. Their paper is one of the closest to this study given its focus on the London residential property market. However, its methodology can be extended by incorporating a treatment-year interaction term to test for anticipation effects, and by using property-level, rather than postcode-aggregated, data to improve spatial precision.

2.4 Spatial Econometrics

Researchers often assume away spatial interactions between observations by including spatial fixed effects. However, there is a growing body of literature arguing for the need to control for possible spatial dependencies (LeSage & Pace, 2009). The existence of spatial lag is supported by the intuition that property valuation is not only based on intrinsic and local characteristics, but also on the transaction prices of nearby comparable properties. This is the premise behind the increasing adoption of spatial difference-in-differences (SDID) models, which is perhaps the most novel innovation in this field.

Much of the early work in spatial econometrics was pioneered by Anselin (1988). Dubé

[1] As DID is estimated using OLS, I use "OLS" to refer specifically to standard cross-sectional and before-and-after models that do not incorporate a treatment-control design.

et al. (2014) applied spatial econometric techniques to the study of transportation on housing values using a spatial lag model (SAR), whereas Diao et al. (2017) included both a spatial lag and error parameter in their spatial autocorrelation combined model (SAC/SARAR). Subsequent studies using differing forms of SDID generally find significant spatial parameters (Arku et al., 2024; Higgins, 2019; Higgins et al., 2024; Huang et al., 2024; Hyun & Milcheva, 2019; Ke & Gkritza, 2019; Qiu & Tong, 2021; Zhu & Diao, 2024).

The primary issue with spatial regressions involves the lack of a mathematically-rigorous, first-best method that is universally accepted, and therefore largely remains an empirical question. Because authors use different methods to obtain the spatial or spatio-temporal weight matrix, this would explain part of the disparities in results. The memory-intensive nature of calculating the matrices, owing to its quadratic time complexity, further stifles its diffusion into the literature. Though the lack of standardisation across spatial models may undermine their application in guiding policymaking, it is nonetheless worthwhile to include when modelling LVU to observe whether spatial dependencies exist, and to benchmark against conventional models.

2.5 Research Gap

There have been several commercial reports on the capitalisation effects of Crossrail before its inauguration.[2] While the results are positive, they exhibit some variation, and the exact methodologies and datasets used are not always detailed. Moreover, these reports tend to focus on the short-term impacts of the Elizabeth line's post-announcement years, with none providing a full view of Crossrail's entire life cycle, which requires data predating its official announcement in 2008.

To the best of my knowledge, there are no existing academic studies that analyse the capitalisation effects of the Elizabeth line on residential property values across its entire lifespan — from proposal to operation. By performing DID analysis on a comprehensive dataset spanning 18 years, this study contributes to the existing literature by adding another datapoint on the magnitude of LVU resulting from the Elizabeth line, and to introduce the Manhattan distance measure as a substitute to the Euclidean distance. The results can help inform policymaking in terms of cost-benefit analysis and supporting the usage of funding methods for future rail transport infrastructure.

[2]See CBRE (2024), GVA (2018) and TfL (2017).

3 The Elizabeth Line

Named after HM Queen Elizabeth II, the Elizabeth line is a 118km-long railway that runs in an east-west direction across London, with its eastern periphery extending to Shenfield and its western terminus in Reading. At an estimated cost of £18.9 billion, the line has been expected to expand central London's rail capacity by 10% and contribute £42 billion to the UK economy (Transport for London, 2022). Jointly sponsored by Transport for London (TfL) and the Department for Transport, the project aligns with the government's broader transport decarbonisation goal and Levelling Up mission to ameliorate regional inequality.

Under the alias of Crossrail, plans first began in 2001 when the Crossrail Ltd joint venture formed between the Department for Transport and TfL. The business case, setting out the line's objectives and funding model, was published in 2005.[3] The system was formally approved by the Crossrail Act 2008, receiving royal assent on 22nd July 2008.[4] Construction works began soon after on 15th May 2009, starting in Canary Wharf. Originally planned to open in 2018, the project faced repeated delays, including as a result of the COVID-19 pandemic. Service officially commenced on 24th May 2022. Bond Street station, however, opened five months later on 24th October 2022.

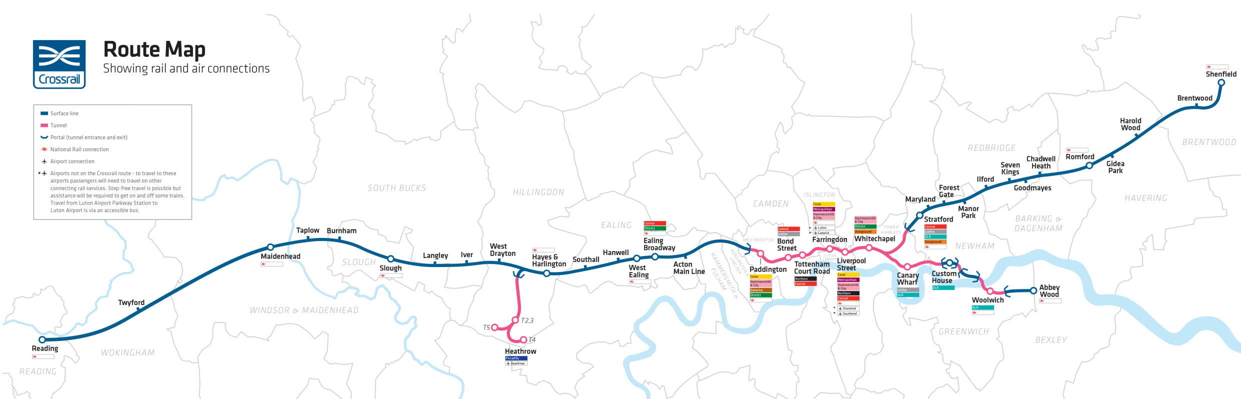

Figure 1: The Elizabeth Line Route

Since opening, the line has made over 350 million journeys. The cumulative benefits of improving train and highway journey times, congestion relief, accident savings, tax revenues, emissions, noise and air quality are estimated to outweigh capital and operating costs by a ratio of 1.9 (Transport for London, 2024).

[3] For further details on Crossrail's early history, see Tucker (2017) and Bennett (2017).
[4] https://www.legislation.gov.uk/ukpga/2008/18/contents

4 Data

4.1 Study Area

My dataset consists of residential property transactions within a 3km buffer zone from all 41 Elizabeth line stations between January 2006 and December 2024. The pooled cross-sectional data comes from Zoopla, one of the UK's largest real estate property portals, and consists of 309,876 housing transactions in total.

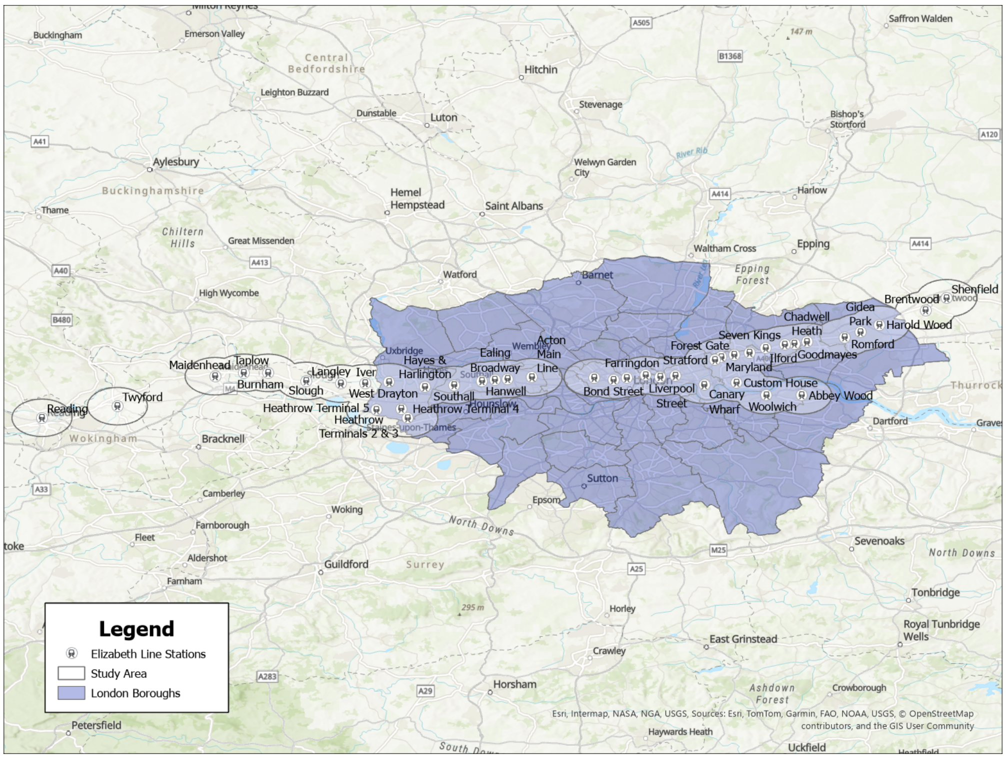

Figure 2: Study Boundary

4.2 Housing Characteristics

Each observation includes the floor area (in square metres), number of bedrooms, bathrooms and living rooms, property type, tenure, Energy Performance Certificate (EPC) rating and longitude and latitude coordinates.

The property type category includes flats, terraced, semi-detached and detached properties; tenure is either leasehold or freehold. EPC ranges from A to G, where A represents the best possible energy efficiency rating. The natural logarithm of the price and floor area variables is taken in order to normalise the distributions, and to capture diminishing marginal utility in attributes.

In addition, the distance to the nearest Elizabeth line station is calculated for each property using the network, Euclidean and Manhattan distance measures. Elizabeth line station coordinates are obtained from the Transport for London website. Road network shapefile data is obtained from Ordnance Survey.

4.3 Neighbourhood Characteristics

I match data on population density and population age composition (0–29, 30–64 and 65+) from the Office for National Statistics using each property's Lower Layer Super Output Area (LSOA), a small geographical unit created for statistical purposes. LSOA boundaries are available on the Open Geography Portal, allowing each property to be matched to its 2001, 2011 and 2021 LSOA. Demographic time series data is available from 2006 to 2022; however, pre-2011 values are matched using 2011 LSOAs, and the rest using 2021 LSOAs. Using 2011–2022 data, the Autoregressive Integrated Moving Average model is applied to forecast 2023 and 2024 values for each 2021 LSOA.

The Index of Multiple Deprivation (IMD) is an index that captures various dimensions of socioeconomic disadvantage, including income, employment, education, health, crime, environment and barriers to housing, providing a comprehensive measure of deprivation, whereby a higher score reflects a more deprived area. Given the IMD's multifaceted nature, median income, crime statistics and educational performance variables are not required, as including them would introduce high multicollinearity. Data on IMD scores are provided for 2004, 2007 and 2010 under 2001 LSOAs, and in 2015 and 2019 for 2011 LSOAs by the Department for Levelling Up, Housing and Communities. Consumer Data Research Centre additionally provides 2010 data adjusted for 2011 LSOAs. This means that IMD scores for all years between 2004 and 2019 can be linearly interpolated. As there are comparatively fewer years of published data for IMD, I avoid introducing noise through extrapolation by assuming that the 2020–2024 values match those of 2019.

4.4 Fixed Effects and Multicollinearity

To control for local attributes unaccounted for by existing neighbourhood data, 168 spatial fixed effects are introduced in total using outward postcodes. Time fixed effects are included on a quarterly basis, with 76 quarterly time dummies spanning from Q1 1995 to Q4 2024.

Due to high correlation between Floor Area and Bedrooms, I drop Bedrooms from the models given its discrete nature. I also drop the Tenure category as Flats, Freehold and Leasehold are highly correlated.

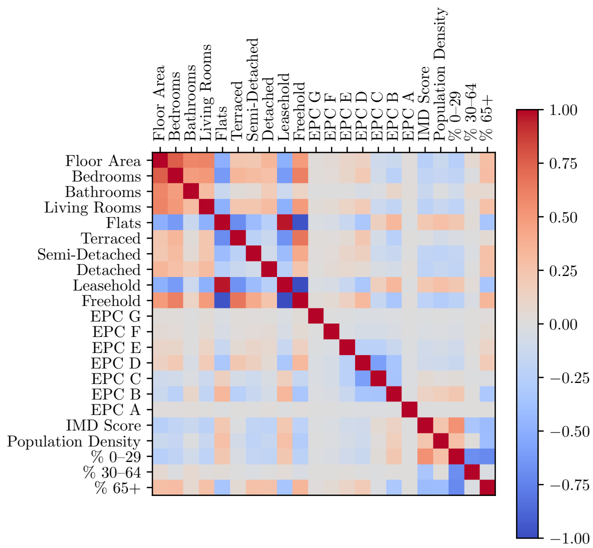

Figure 3: Covariate Correlation Matrix

For each categorical variable, one dummy is dropped to serve as a reference category, preventing perfect multicollinearity. For Property Type, the Flats category is dropped, and for EPC, the G rating. For the population age bands, the 30–64 group serves as the baseline.

4.5 Distance Measures

Suppose there are two observations i and j with respective longitude and latitude coordinates (x_i, y_i) and (x_j, y_j). The Euclidean and Manhattan distance measures are calculated in two-dimensional space using the formulas:

$$d_{ij}^{\text{Euclidean}} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

$$d_{ij}^{\text{Manhattan}} = |x_i - x_j| + |y_i - y_j|$$

Except for when i and j are identical or perfectly aligned, the Manhattan distance must necessarily be greater than the Euclidean distance due to the triangle inequality. Diao et al. (2017) argues that as the Euclidean distance underestimates the true distance faced by commuters, using this measure may lead to biased results.

In the below example, the network distance between the 1 Park Drive residential skyscraper and Canary Wharf Elizabeth line station is calculated as 768m in ArcGIS Pro. The Euclidean distance is calculated as 526m, and the Manhattan distance as 719m. The latter measure is a closer approximation of the network distance and, unlike the former, does not assume the commuter traverses water or buildings.

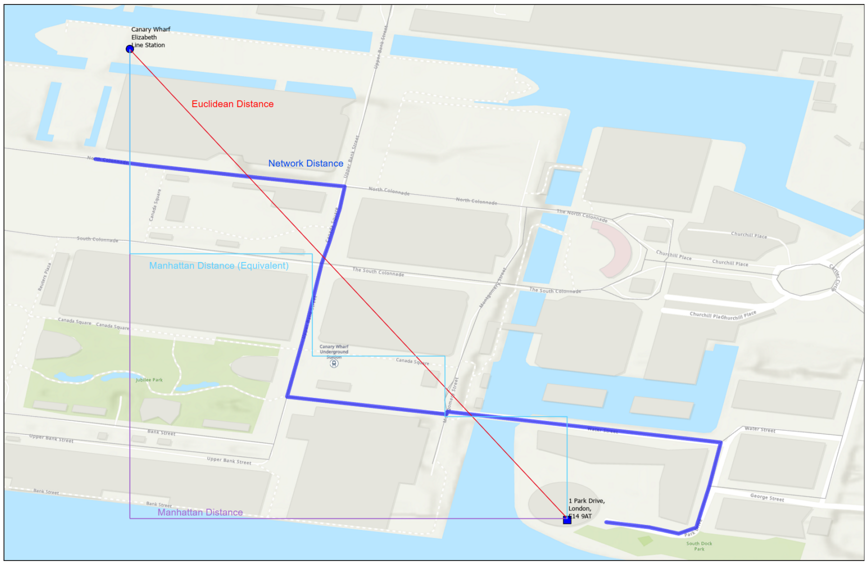

Figure 4: Distance Measure Comparison

In general, the Manhattan distance becomes a better proxy for the network distance the more grid-like the study area's layout is. However, both Euclidean and Manhattan distance will fall short if there is a large insurmountable obstacle, such as crossing the River Thames in areas without a bridge or tunnel nearby.

4.6 Treatment and Control Zones

Many studies use 1/2 mile or 800m as the cutoff distance to sort between groups; the line of reasoning is that this figure represents a walkable distance (Guerra et al., 2012). Although this argument has merit, the true treatment zone may not be homogenous across study areas. Rather than arbitrarily assigning a threshold, a more robust selection method may involve dynamically setting a boundary based on a hedonic pricing model. I adapt Xu and Zhang's (2016) methodology by sorting observations into 150m distance bands and set properties beyond 2850m as the reference category for the Euclidean and Manhattan distances. As the maximum value under the network distance is around 7100m, I use 300m distance bands and set transactions beyond 5700m as the reference category. Including housing and neighbourhood controls alongside spatial and time fixed effects enables us to identify the price premium associated with each band. It is expected that the coefficients should be systematically positive and significant up until a certain group, after which it remains insignificant or negative.

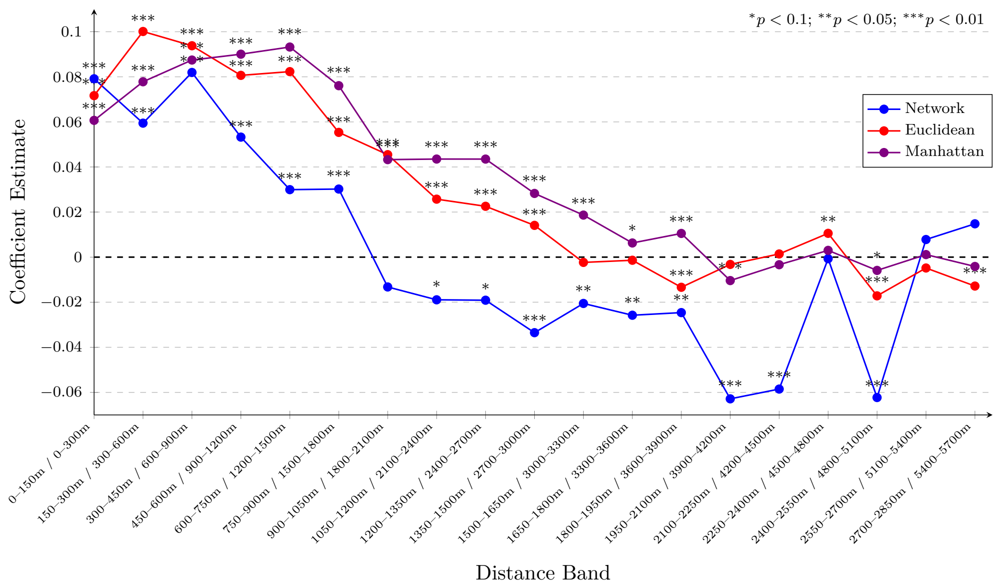

Figure 5: Location Premium by Distance Band

Figure 5 shows that the hedonic price for proximity to stations initially increases with distance, before gradually descending. The coefficients are positive and significant up until 1800m, 1500m and 1950m for the network, Euclidean and Manhattan distance measures respectively. This result is similar to a report by Nationwide (2021), finding that the location premium associated with London Underground stations extends up to a straight-line distance of 1500m.

4.7 Descriptive Statistics

Table 1 presents the descriptive statistics for the entire dataset, and the treatment and control groups defined by network distance. At a glance, the characteristics of all groups appear similar.

	Full Dataset			Treatment Group			Control Group		
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
Price	309,876	508,688.00	739,005.70	120,331	481,896.00	629,137.20	189,545	525,696.60	800,508.40
Floor Area	309,876	90.92	45.51	120,331	88.95	44.08	189,545	92.18	46.35
Bedrooms	309,876	2.36	1.05	120,331	2.29	1.05	189,545	2.40	1.05
Bathrooms	309,876	1.41	0.66	120,331	1.40	0.64	189,545	1.41	0.67
Living Rooms	309,876	1.26	0.54	120,331	1.25	0.53	189,545	1.27	0.55
IMD Score	309,876	23.65	11.67	120,331	23.26	11.47	189,545	23.90	11.79
Population Density	309,876	10,669.78	8,224.42	120,331	10,581.48	8,398.32	189,545	10,725.83	8,111.62
% 0–29	309,876	42.37	7.66	120,331	43.05	8.09	189,545	41.93	7.33
% 30–64	309,876	47.61	5.42	120,331	47.30	5.56	189,545	47.81	5.33
% 65+	309,876	10.03	5.56	120,331	9.65	5.44	189,545	10.28	5.63
Network Distance	309,876	2,232.12	1,143.95	120,331	1,124.96	427.56	189,545	2,934.99	866.66
Euclidean Distance	309,876	1,588.09	772.03	120,331	824.68	350.61	189,545	2,072.73	539.91
Manhattan Distance	309,876	1,977.45	963.87	120,331	1,044.33	450.83	189,545	2,569.84	697.22

Table 1: Summary Statistics

5 Estimation Strategy

5.1 Difference-in-Differences Model Specification

For the baseline results, we start with a standard DID model:

$$\begin{aligned} \ln(P) = \alpha &+ \beta_1(\text{Treat} \times \text{Announcement}) + \beta_2(\text{Treat} \times \text{Construction}) \\ &+ \beta_3(\text{Treat} \times \text{Post}) + H'\gamma + N'\theta + \varphi + \tau + \varepsilon \end{aligned} \tag{1}$$

where $\ln(P)$ is log property price, $H'\gamma$ represents housing characteristics, $N'\theta$ represents neighbourhood characteristics, φ are spatial fixed effects, τ are time fixed effects and ε is the i.i.d. error term.

Treat is a binary variable which takes on the value of 1 if the property is within the treatment zone threshold distance from an Elizabeth line station, and 0 otherwise. Announcement is another binary variable that equals 1 if the transaction date occurs between 22$^{\text{nd}}$ July 2008 and 15$^{\text{th}}$ May 2009, and 0 otherwise. Construction equals 1 if the transaction date is between 15$^{\text{th}}$ May 2009 and 24$^{\text{th}}$ May 2024. Post equals 1 if the transaction date occurs on 24$^{\text{th}}$ May 2024 or afterwards (or on or after 24$^{\text{th}}$ October 2022 if the closest station is Bond Street), and 0 otherwise. The pre-announcement phase will include all transactions falling before 22$^{\text{nd}}$ July 2008. The coefficients of interest — β_1, β_2 and β_3 — give us the average treatment effect on the treated. My hypothesis is that they are all positive and significant. I regress this base model using the network, Euclidean and Manhattan distance measures to compare their results.

5.1.1 Treatment Effects over Space

To test for spatial variations in treatment effects, I divide the treatment group into 5 zones:

$$\begin{aligned} \ln(P) = \alpha &+ \sum_{i=1}^{5} \beta_i(\text{Zone } i \times \text{Announcement}) + \sum_{j=1}^{5} \delta_j(\text{Zone } j \times \text{Construction}) \\ &+ \sum_{k=1}^{5} \sigma_k(\text{Zone } k \times \text{Post}) + H'\gamma + N'\theta + \varphi + \tau + \varepsilon \end{aligned} \tag{2}$$

where each Zone extends 300m distance, except for Zone 5, which covers 1200–1800m/1500m/1950m based on treatment threshold identified for each distance measure in Figure 5.

5.1.2 Treatment Effects across Regions

To identify whether capitalisation effects are stronger in some areas compared to others, I group the dataset into 5 regions based on each transaction's closest station in terms of network distance, and rerun equation (1) on the five subdatasets.

The regions are divided into West of London (Reading to Iver), West London (West Drayton and Heathrow to Acton Main Line), Central London (Paddington to Liverpool Street), East London (Whitechapel to Harold Wood and Abbey Wood) and East of London (Brentwood and Shenfield).

5.2 Spatial Difference-in-Differences Model Specification

Combining the baseline DID regression with the STAR model yields the SDID specification:

$$\begin{aligned} \ln(P) &= \rho W \ln(P) + X'\eta + u \\ u &= \lambda W u + \varepsilon \end{aligned} \tag{3}$$

where ρ is the spatial autoregressive parameter, $W \ln(P)$ is the spatially lagged dependent variable, X represents all the explanatory variables in equation (1) with coefficient vector η, u is the spatially correlated error term, λ is the spatial error parameter and Wu is the spatially lagged error term, with all parameters estimated using maximum likelihood estimation.

Due to memory constraints from the large sample size, the SDID model is applied to the three stations with the most properties nearest to them by network distance: Paddington, Canary Wharf and Reading.

5.2.1 The Spatial Weight Matrix and Spatial Weights

The spatial weight matrix, S, is an $n \times n$ positive, symmetric and non-stochastic matrix, where the element s_{ij} at location (i, j) acts as the spatial weight and n is the number of observations. The magnitude of the weights represents the pairwise degree of proximity. By convention, the diagonal cells equal 0, as self-neighbourhood is excluded. This is the key term that formalises spatial dependence into a model:

$$S = \begin{bmatrix} 0 & s_{12} & \cdots & s_{1n} \\ s_{21} & 0 & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n1} & s_{n2} & \cdots & 0 \end{bmatrix}$$

As there is a temporal dimension, the data needs to be sorted chronologically before calculations are performed. For the distance-based spatial weights, I use the negative exponential model for calculating weights:

$$s_{ij} = \begin{cases} \exp(-d_{ij}) & \text{if } i \neq j \text{ and } d_{ij} \leq \overline{d}, \\ 0 & \text{otherwise,} \end{cases}$$

where d_{ij} is the Euclidean distance in kilometres between properties i and j and $\overline{d}$ is a threshold distance determined by fitting an empirical semivariogram. Figure 6 indicates that the range — the distance at which spatial correlation plateaus — is approximately 1000m.

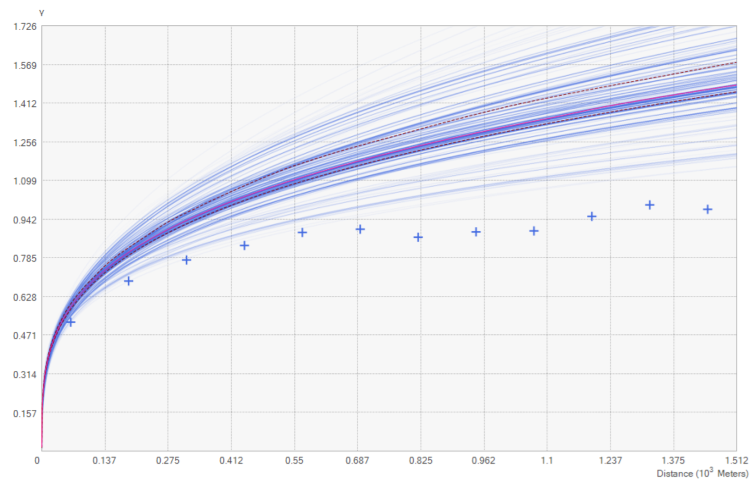

Figure 6: Empirical Semivariogram

5.2.2 The Temporal Weight Matrix

The temporal weight matrix is structurally analogous to the spatial weight matrix, with each element representing the temporal distance between two transactions:

$$T = \begin{bmatrix} 0 & t_{12} & \cdots & t_{1n} \\ t_{21} & 0 & \cdots & t_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1} & t_{n2} & \cdots & 0 \end{bmatrix}$$

The temporal weights are calculated as follows:

$$t_{ij} = \begin{cases} (v_i - v_j)^{-1} & \text{if } i > j \text{ and } 0 < v_i - v_j \leq \overline{v}, \\ 1 & \text{if } v_i = v_j \text{ and } i \neq j, \\ (v_j - v_i)^{-2} & \text{if } i < j \text{ and } 0 < v_j - v_i \leq \underline{v}, \\ 0 & \text{otherwise,} \end{cases}$$

where v_i is the number of months between i and the earliest month of the dataset and $\overline{v}$ and $\underline{v}$ denote the thresholds for past and future influence. This formulation assumes that transactions may be influenced by sales occurring up to 6 months prior and 3 months after, enforcing a harsher penalty on future influences. Whilst this does not strictly adhere to the unidirectionality of time emphasised by Thanos et al. (2016), implementing their approach results in isolates within the final matrix. I therefore follow the method used by Higgins (2019), which permits limited future influence to capture expectation and peer effects.

The spatio-temporal weight matrix is computed as the Hadamard product of the spatial and temporal weight matrices (Smith & Wu, 2009):

$$W = S \odot T$$

which is then row standardised.

5.3 Triple Difference Model Specification

Lastly, some of the station-level heterogeneity may be explained by network effects accentuating LVU for stations with more connecting lines. We can add a three-way interaction term in a difference-in-difference-in-differences (DDD), or triple difference, setting to test this:

$$\begin{aligned} \ln(P) = \alpha &+ \beta_1(\text{Treat} \times \text{Announcement}) + \beta_2(\text{Treat} \times \text{Construction}) \\ &+ \beta_3(\text{Treat} \times \text{Post}) + \sum_{i=1}^{6} \delta_i(\text{Treat} \times \text{Announcement} \times \text{Connections}) \\ &+ \sum_{j=1}^{6} \sigma_j(\text{Treat} \times \text{Construction} \times \text{Connections}) \\ &+ \sum_{k=1}^{6} \psi_k(\text{Treat} \times \text{Post} \times \text{Connections}) + H'\gamma + N'\theta + \varphi + \tau + \varepsilon \end{aligned} \tag{4}$$

where Connections is the number of lines the transaction's closest station connects to.

6 Results

6.1 DID Model Results

Table 2 presents the results from equation (1). All coefficients are positive and significant as hypothesised. The results indicate that capitalisation effects in treatment areas were highest during the construction phase (2.86–5.31%), followed by the announcement phase (2.21–3.15%) and lowest post-opening (0.81–3.01%). This implies that expectations were capitalised early on, peaking during construction as the line's completion became more certain. However, post-opening, the benefits have been mostly exhausted, and potential negative externalities from operations may temper further gains.

	(1)	(2)	(3)
Treat × Announcement	0.0315***	0.0285***	0.0221***
	(0.0078)	(0.0075)	(0.0074)
Treat × Construction	0.0531***	0.0347***	0.0286***
	(0.0017)	(0.0017)	(0.0016)
Treat × Post	0.0301***	0.0103***	0.0081***
	(0.0032)	(0.0031)	(0.0031)
Property Characteristics	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Distance Measure	Network	Euclidean	Manhattan
Observations	309,876	309,876	309,876
R^2	0.7995	0.7991	0.7991
Adjusted R^2	0.7994	0.7990	0.7989
Residual Std. Error (df = 309614)	0.2976	0.2978	0.2979
F Statistic (df = 261; 309614)	4,730.8300***	4,719.7950***	4,717.2050***

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 2: Capitalisation Effects over Time

Furthermore, the network distance measure produces higher coefficient estimates than the Euclidean distance. While this aligns with the findings of Diao et al. (2017), it contrasts with Hess and Almeida (2007). Although Diao et al. applied a consistent 600m treatment threshold across both measures, my analysis uses different thresholds for each distance measure. Importantly, these thresholds represent different proportions of their respective distance ranges: 1500m is half of the maximum Euclidean distance defined by my study boundary

(3000m), while 1800m represents about a quarter of the maximum network distance (7093m). As such, the treatment group defined using network distance likely includes properties that are, on average, closer to stations than those included using the Euclidean measure. This may partially explain why the network-based estimates are noticeably higher.

Contrary to expectations, we observe that Euclidean distance yields estimates closer to the network distance than Manhattan distance for all three coefficients. This suggests that while Manhattan distance may sometimes better approximate actual travel patterns, there is little evidence that it systematic outperforms Euclidean distance in this context.

6.1.1 Hedonic Prices

Although the coefficients for housing and neighbourhood characteristics are not the primary focus of this study, they are not without interest. The coefficients for Floor Area, Bathrooms, Living Rooms and Property Type are positive and significant, as expected. The EPC coefficients warrant more interest. Whilst an EPC rating of B commands a 14.21% premium compared to properties with the lowest, G, rating, all the other grades are statistically insignificant. This could be because official EPC data includes expired certificates that no longer reflect a property's current condition, and buyers may instead value a property's potential EPC rating — neither of which is accounted for in the model. Additionally, the lack of a significant effect for EPC A may reflect the limited number of observations (230).

Turning to neighbourhood characteristics, the results suggest that local factors also play a role in shaping house prices, albeit to a lesser extent. Areas with a higher proportion of residents aged 0–29 or 65+ (relative to the 30–64 age group) are associated with lower property values, indicating weaker demand in areas with younger or older populations. Population density is also negatively associated with price, though the effect size is minimal. Higher levels of deprivation are associated with lower prices, with each additional point on the IMD score linked to a 0.59% reduction in housing values.

Moreover, the Variance Inflation Factors for each covariate across all models are below 4, suggesting that multicollinearity is not a significant issue.[5]

[5] While Table 3 is based on model (1) in Table 2, the values for models (2) and (3) are virtually identical, and the same conclusions hold.

	Dependent Variable: $\ln(P)$
ln(Floor Area)	0.6120^{***}
	(0.0021)
Bathrooms	0.1002^{***}
	(0.0011)
Living Rooms	0.0373^{***}
	(0.0013)
Terraced	0.1375^{***}
	(0.0017)
Semi-Detached	0.1789^{***}
	(0.0023)
Detached	0.2525^{***}
	(0.0032)
EPC F	0.0239
	(0.0154)
EPC E	0.0157
	(0.0140)
EPC D	−0.0005
	(0.0139)
EPC C	−0.0019
	(0.0139)
EPC B	0.1421^{***}
	(0.0140)
EPC A	−0.0005
	(0.0241)
IMD Score	-0.0059^{***}
	(0.0001)
Population Density	-0.000003^{***}
	(0.000000)
% 0–29	-0.0018^{***}
	(0.0001)
% 65+	-0.0023^{***}
	(0.0002)
Constant	9.3262^{***}
	(0.0188)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3: Hedonic Prices

6.1.2 Treatment Effects over Space

Across all distance measures, the largest and most significant price increases are observed in Zones 1–3 (within 900m), especially during construction. This aligns with the literature, which finds that LVU peaks at around 500m (Mohammad et al., 2013; Rennert, 2022). When significant, these coefficients usually exceed the average estimate for the entire treatment group. Zones 4 and 5 (beyond 900m), in contrast, generally exhibit weaker and less consistent effects, particularly after completion. This diminishing pattern of effects over space reflects the localised nature of accessibility gains. The lower LVU estimates during construction compared to at announcement for Zone 1 under Euclidean and Manhattan distances hint at the existence of negative externalities associated with construction efforts.

	(1)	(2)	(3)
Zone 1 × Announcement	0.0397	0.0769***	0.0630**
	(0.0362)	(0.0252)	(0.0305)
Zone 1 × Construction	0.0768***	0.0714***	0.0596***
	(0.0060)	(0.0040)	(0.0049)
Zone 1 × Post	0.0596***	0.0349***	0.0231*
	(0.0149)	(0.0095)	(0.0119)
Zone 2 × Announcement	0.0388*	0.0491***	0.0365**
	(0.0210)	(0.0143)	(0.0186)
Zone 2 × Construction	0.0544***	0.0666***	0.0685***
	(0.0036)	(0.0028)	(0.0033)
Zone 2 × Post	0.0202**	0.0367***	0.0443***
	(0.0079)	(0.0059)	(0.0072)
Zone 3 × Announcement	0.0435***	0.0470***	0.0771***
	(0.0152)	(0.0124)	(0.0139)
Zone 3 × Construction	0.0812***	0.0561***	0.0663***
	(0.0029)	(0.0024)	(0.0027)
Zone 3 × Post	0.0491***	0.0193***	0.0321***
	(0.0062)	(0.0050)	(0.0058)
Zone 4 × Announcement	0.0162	−0.0013	0.0016
	(0.0147)	(0.0128)	(0.0137)
Zone 4 × Construction	0.0612***	0.0262***	0.0306***
	(0.0026)	(0.0023)	(0.0025)
Zone 4 × Post	0.0347***	0.0071	0.0013
	(0.0057)	(0.0048)	(0.0054)
Zone 5 × Announcement	0.0360***	0.0342***	0.0148
	(0.0101)	(0.0123)	(0.0094)
Zone 5 × Construction	0.0418***	0.0104***	0.0136***
	(0.0019)	(0.0022)	(0.0018)
Zone 5 × Post	0.0263***	0.0016	0.0041
	(0.0040)	(0.0048)	(0.0037)
Property Characteristics	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Distance Measure	Network	Euclidean	Manhattan
Observations	309,876	309,876	309,876
R^2	0.7997	0.7995	0.7995
Adjusted R^2	0.7995	0.7993	0.7993
Residual Std. Error (df = 309602)	0.2975	0.2976	0.2976
F Statistic (df = 273; 309602)	4,526.5060***	4,522.3580***	4,521.0150***

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 4: Spatial Variation in Effects

Some patterns may partly reflect differences in sample composition and size. The Euclidean distance metric yields the most evenly distributed sample groups across treatment zones, resulting in the smallest standard errors overall. Given its linear nature, it is unsurprising that LVU consistently diminishes with distance (with the exception of Zone 5 × Announcement). On the other hand, relatively few properties fall into Zone 1 under the network and Manhattan definitions, whilst Zone 5 accounts for the largest share of treated transactions. This is because they, by definition, produce higher values than the planar distance. The result of this skew could be a lag effect, whereby many properties that are proximate to stations on a straight-line basis — and thus assigned to Zones 1 to 3 under Euclidean distance — are shifted to Zones 2 to 4 under the non-Euclidean measures. As a result, Zones 2 to 4 would capture a higher share of well-connected properties, thereby explaining why they experience similar, or even stronger, capitalisation effects than closer zones both within and across distance measures.

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Total
Network	3,864	12,435	21,336	25,989	56,707	120,331
	(3.2%)	(10.3%)	(17.7%)	(21.6%)	(47.1%)	
Euclidean	9,653	25,082	36,579	39,198	36,798	147,310
	(6.6%)	(17.0%)	(24.8%)	(26.6%)	(25.0%)	
Manhattan	5,991	16,474	26,123	30,987	76,300	155,875
	(3.8%)	(10.6%)	(16.8%)	(19.9%)	(48.9%)	

Similarly to Table 2, the network distance is the most strongly associated with uplift. Although Manhattan distance coefficients now resemble network distance more than Euclidean distance in many cases, there is no consistent pattern of outperformance.

6.1.3 Treatment Effects across Regions

Table 5 reveals considerable heterogeneity in LVU across regions. Most notably, properties in Central London and East benefit the most, with 8.25% and 10.99% in uplift during construction. Capitalisation effects remain the strongest after opening for Central London and East at 6.18% and 6.64%, whereas the West region faces negative effects of –1.68%. These post-opening dynamics likely reflect enhanced accessibility compounding existing connectivity in Central London, or generating new connections to previously underserved stations such as Brentwood, generating network effects that persist upon operations. This may also help explain the lack of significant announcement effects in Central and West London, where benefits were already priced in or perceived as marginal at the time. In contrast, areas west of London after May 2022 may face weaker ridership, potential disamenities or a market correction following earlier price anticipation.

	(1)	(2)	(3)	(4)	(5)
Treat × Announcement	0.0311**	−0.0274	0.0143	0.0391***	0.1433***
	(0.0132)	(0.0181)	(0.0205)	(0.0113)	(0.0378)
Treat × Construction	0.0252***	0.0503***	0.0825***	0.0636***	0.1099***
	(0.0027)	(0.0037)	(0.0062)	(0.0022)	(0.0075)
Treat × Post	−0.0168***	0.0415***	0.0618***	0.0261***	0.0664***
	(0.0054)	(0.0068)	(0.0106)	(0.0044)	(0.0143)
Property Characteristics	Yes	Yes	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Region	West	West London	Central London	East London	East
Observations	46,918	54,768	65,123	133,834	9,233
R^2	0.8283	0.8008	0.7757	0.7230	0.8239
Adjusted R^2	0.8280	0.8004	0.7751	0.7227	0.8221
Residual Std. Error	0.2104 (df = 46811)	0.2694 (df = 54645)	0.3774 (df = 64947)	0.2687 (df = 133689)	0.2411 (df = 9136)
F Statistic	2,131.0240*** (df = 106; 46811)	1,801.1690*** (df = 122; 54645)	1,283.7930*** (df = 175; 64947)	2,422.8330*** (df = 144; 133689)	445.3435*** (df = 96; 9136)

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 5: Regional Variation in Effects

6.2 SDID Model Results

Table 6 shows that SDID estimates are consistently lower and less significant than those from the standard DID model, aligning with Diao et al. (2017) but diverging from Dubé et al. (2014). This likely reflects model differences; Diao et al. use SAC/SARAR, whereas Dubé et al. use SAR, with higher coefficients in Diao et al.'s SAR model supporting this. The significant spatial lag coefficient indicates that property values are positively influenced by neighbouring areas, while the strong spatial error term suggests spatially correlated unobserved factors. Although the Bayesian information criterion (BIC) favours DID due its harsher penalty on model complexity, the substantially lower Akaike information criterion (AIC) and highly significant likelihood ratio (LR) test provide strong evidence that SDID offers a superior fit.

	(1)	(2)
Treat × Announcement	0.1601***	0.0848*
	(0.0314)	(0.0401)
Treat × Construction	0.1654***	0.0900***
	(0.0057)	(0.0080)
Treat × Post	0.0874***	0.0241
	(0.0137)	(0.0197)
ρ		0.4550***
		(0.0457)
λ		0.8896***
		(0.0214)
Property Characteristics	Yes	Yes
Neighbourhood Attributes	Yes	Yes
Spatial Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Station	Canary Wharf	Canary Wharf
Observations	21,392	21,392
Adjusted / Pseudo R^2	0.5874	0.6630
AIC	9,060.7064	5,168.1944
BIC	5,973.2424	9,849.8128
LR Test Statistic	3,896.5120***	

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Station-Level SDID

The station-level results highlight further nuances in LVU effects. Both Paddington and Canary Wharf demonstrate that regional-level analysis can still mask local variation, as both deviate from their regional averages. Most strikingly, Canary Wharf exhibits substantial LVU at every stage using DID — roughly double the regional average and triple the study boundary's average. Canary Wharf's unusually high LVU likely reflects a combination of accessibility benefits that amplify its existing Jubilee line and DLR connections, strong residential and commercial demand and investments tied to local redevelopment plans.

6.3 DDD Model Results

The DDD model reveals positive network effects, but nonlinearities in marginal gains from connectivity. Stations with no interchange options experienced no significant announcement effects, and little to no uplift during construction (up to 2.2%). However, they experience very strong post-opening uplift (4.8–7.2%), likely because the Elizabeth line delivered substantial transformations in accessibility for these relatively isolated stations. Excluding the station with six connections, this is reinforced by the negative post-opening coefficients for stations with interchanges, and the negative or insignificant coefficients for stations with just one interchange — reflecting the fact that the greatest beneficiaries of the line were those with the fewest pre-existing connections. As usual, the network distance tends to produce the highest estimates, with the Mahattan and Euclidean measures providing close approximations at times. The lack of a predictive pattern ultimately reflects the fact that they are three distinct measures, providing three different interpretations of the same underlying phenomenon.

As connectivity increases, anticipatory effects become more pronounced. At a high level, the existence of positive network effects — in the form of additional LVU for interchange stations — is supported by the positive announcement and construction coefficients for stations with two to six connections. However, a closer comparison of coefficients between adjacent groups reveals that the marginal effect is not always positive. This stems from the key limitation that the DDD model implicitly assumes the quality of connections is equally valuable, which does not hold in practice. Lines with higher ridership, greater frequency and better central access are likely to contribute more towards this network effect; a more fine-tuned model would incorporate a weighted index of connectivity using these variables.

	(1)	(2)	(3)
Treat × Announcement	-0.0127	-0.0175	0.0114
	(0.0152)	(0.0150)	(0.0162)
Treat × Construction	0.0220^{***}	0.0001	0.0173^{***}
	(0.0033)	(0.0032)	(0.0033)
Treat × Post	0.0716^{***}	0.0475^{***}	0.0573^{***}
	(0.0059)	(0.0058)	(0.0063)
Treat × Announcement × 1	0.0308^{*}	0.0355^{**}	0.0081
	(0.0176)	(0.0169)	(0.0187)
Treat × Construction × 1	-0.0099^{***}	0.0044	-0.0131^{***}
	(0.0038)	(0.0036)	(0.0038)
Treat × Post × 1	-0.0522^{***}	-0.0378^{***}	-0.0472^{***}
	(0.0068)	(0.0065)	(0.0072)
Treat × Announcement × 2	0.1226^{***}	0.0784^{***}	0.0890^{***}
	(0.0210)	(0.0197)	(0.0228)
Treat × Construction × 2	0.0917^{***}	0.0567^{***}	0.0671^{***}
	(0.0048)	(0.0045)	(0.0048)
Treat × Post × 2	-0.0384^{***}	-0.0637^{***}	-0.0506^{***}
	(0.0092)	(0.0082)	(0.0094)
Treat × Announcement × 3	0.0150	0.0165	0.0057
	(0.0271)	(0.0258)	(0.0299)
Treat × Construction × 3	0.0908^{***}	0.0873^{***}	0.0822^{***}
	(0.0058)	(0.0057)	(0.0060)
Treat × Post × 3	-0.0756^{***}	-0.0596^{***}	-0.0761^{***}
	(0.0105)	(0.0100)	(0.0114)
Treat × Announcement × 4	0.0865^{**}	0.1234^{***}	-0.0135
	(0.0339)	(0.0319)	(0.0374)
Treat × Construction × 4	0.1707^{***}	0.1916^{***}	0.1187^{***}
	(0.0094)	(0.0083)	(0.0099)
Treat × Post × 4	-0.0372^{**}	-0.0155	-0.0578^{***}
	(0.0163)	(0.0152)	(0.0183)
Treat × Announcement × 5	0.0844^{***}	0.1008^{***}	-0.0068
	(0.0253)	(0.0235)	(0.0280)
Treat × Construction × 5	0.1032^{***}	0.0874^{***}	0.0711^{***}
	(0.0059)	(0.0054)	(0.0060)
Treat × Post × 5	-0.0399^{***}	-0.0575^{***}	-0.0451^{***}
	(0.0113)	(0.0103)	(0.0116)
Treat × Announcement × 6	0.2374^{***}	0.1870^{***}	0.1712^{***}
	(0.0442)	(0.0453)	(0.0492)
Treat × Construction × 6	0.2577^{***}	0.2581^{***}	0.2464^{***}
	(0.0088)	(0.0078)	(0.0090)
Treat × Post × 6	0.0408^{**}	0.0328^{*}	0.0189
	(0.0182)	(0.0168)	(0.0195)
Property Characteristics	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Distance Measure	Network	Euclidean	Manhattan
Observations	309,876	309,876	309,876
R^2	0.8009	0.8005	0.8003
Adjusted R^2	0.8007	0.8003	0.8001
Residual Std. Error (df = 309596)	0.2965	0.2969	0.2970
F Statistic (df = 279; 309596)	$4{,}464.5050^{***}$	$4{,}451.9180^{***}$	$4{,}446.5530^{***}$

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 7: Marginal Effect of Interchanges

Furthermore, as illustrated by Canary Wharf, the extreme uplift despite just two connections not only skews the DDD estimates, but also brings attention to the broader reality that a plethora of other factors above and beyond interchange count play a significant role in driving capitalisation effects. Liverpool Street, the sole station with six connections, stands out as the interchange location with the highest capitalisation effects, peaking at an estimated 27.97% during construction.[6] This epitomises its role as London's central hub, with exceptional multimodal connectivity, employment density and sustained real estate demand — reiterating the notion that both local context and network topology matter. Nevertheless, even with its simplifying assumptions, the DDD framework offers valuable insight by helping uncover clear patterns of network effects as one pivotal influence of the spatial heterogeneity in LVU observed in Tables 5 and 6.

[6] Though using DID for Liverpool Street based on network distance yields lower estimates of 16.01%, 16.54% and 8.74% at announcement, construction and post respectively.

7 Robustness Checks

7.1 Parallel Trends

Because the choice of station location is almost always influenced by factors such as population density, deprivation levels and potential for development, the non-random nature of station placement complicates proving parallel trends and establishing causal relationships compared to randomised controlled trials. A formal test for common trends prior to an intervention involves adding interaction terms between the treatment variable and time fixed effects to estimate the temporal trend in the treated group relative to the control group:

$$\ln(P) = \alpha + \beta \text{Treat} + \sum_{i=1} \delta_i (\text{Treat} \times \tau_i) + H'\gamma + N'\theta + \varphi + \tau + \varepsilon \tag{5}$$

Quarter	(1)	(2)	(3)
Treat × 2006 Q2	0.0013	0.0018	−0.0070
	(0.0103)	(0.0100)	(0.0100)
Treat × 2006 Q3	0.0040	0.0027	0.0067
	(0.0099)	(0.0097)	(0.0096)
Treat × 2006 Q4	0.0202**	0.0165*	0.0140
	(0.0100)	(0.0097)	(0.0097)
Treat × 2007 Q1	0.0028	−0.0004	−0.0041
	(0.0103)	(0.0100)	(0.0100)
Treat × 2007 Q2	0.0056	0.0065	0.0063
	(0.0101)	(0.0098)	(0.0098)
Treat × 2007 Q3	0.0012	0.0010	−0.0038
	(0.0100)	(0.0097)	(0.0097)
Treat × 2007 Q4	−0.0099	−0.0114	−0.0111
	(0.0104)	(0.0102)	(0.0101)
Treat × 2008 Q1	0.0005	−0.0001	0.0004
	(0.0114)	(0.0112)	(0.0112)
Treat × 2008 Q2	−0.0119	−0.0073	−0.0112
	(0.0114)	(0.0112)	(0.0112)
Treat × 2008 Q3	0.0073	0.0077	−0.0046
	(0.0234)	(0.0230)	(0.0230)
Property Characteristics	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Distance Measure	Network	Euclidean	Manhattan
Observations	50,995	50,995	50,995
R^2	0.7855	0.7844	0.7841
Adjusted R^2	0.7847	0.7836	0.7833
Residual Std. Error (df = 50799)	0.2456	0.2462	0.2464
F Statistic (df = 195; 50799)	953.9007***	947.7870***	946.2954***

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 8: Parallel Trends Test

If the coefficients of the interaction terms are statistically insignificant, this suggests no diverging patterns between the treatment and control groups in the pre-treatment period (Dubé et al., 2024; Huang et al., 2024; Zhu & Diao, 2024). Table 8 shows that all coefficients under Manhattan distance are insignificant, and all but 2006 Q4 are insignificant for network and Euclidean distance. However, as this is the only significant pre-intervention quarter, it is safe to say that the parallel trends assumption is broadly satisfied.

We can visually depict this by constructing a housing price index for the treatment and control groups based on the quarterly fixed effects. Figure 7 also traces the evolution of treatment effects within individual phases. For example, in the construction phase, the size of LVU starts to slowly decline between late 2013 and early 2016, before sharply increasing and stabilising from 2017 onwards. The vertical gap between trends tells us that capitalisation effects are stronger towards the end, rather than start, of construction, and appears to peak in the years directly before the line opened.

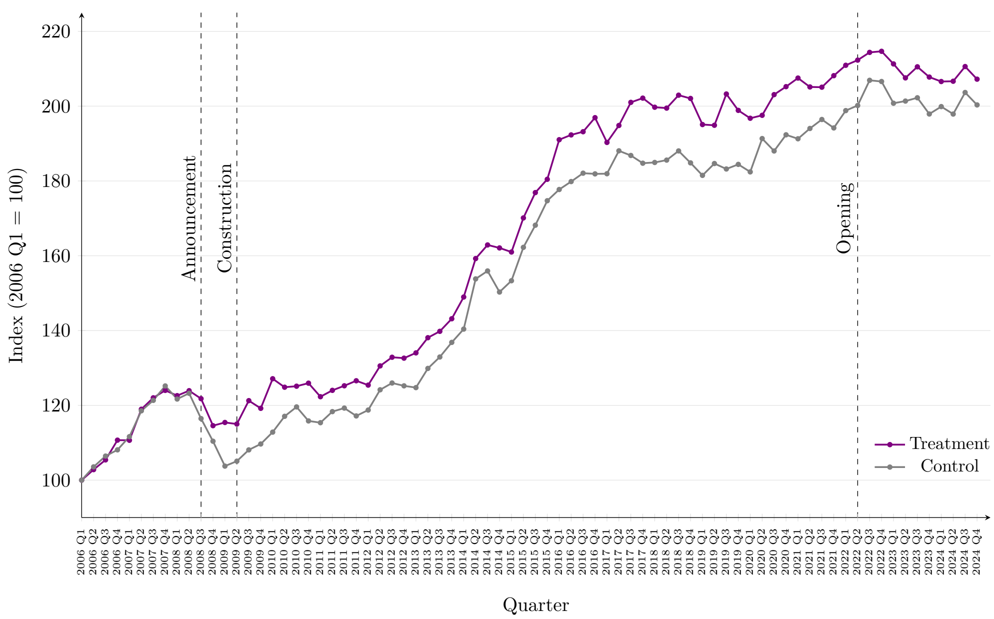

Figure 7: Quarterly Housing Price Index

7.2 Propensity Score Weighting

As an additional robustness check, the baseline DID model is re-estimated using inverse probability weighting, where weights were derived from a logistic regression predicting treatment assignment based on pre-treatment housing and neighbourhood characteristics to adjust for observable differences between treated and control properties:

$$\hat{p} = \Pr(\text{Treat} = 1 \mid H, N) = \Lambda\left(\alpha + H'\gamma + N'\theta\right)$$

Inverse probability weights are then constructed as:

$$w_i = \begin{cases} 1 & \text{if Treat} = 1, \\ \frac{\hat{p}}{1-\hat{p}} & \text{if Treat} = 0. \end{cases}$$

The resulting weighted estimates (Table 9) closely resemble those from the original unweighted model (Table 2) in both magnitude and statistical significance, suggesting that the main findings are not sensitive to selection on observables.

	(1)	(2)	(3)
Treat × Announcement	0.0196***	0.0222***	0.0174**
	(0.0074)	(0.0075)	(0.0075)
Treat × Construction	0.0559***	0.0410***	0.0354***
	(0.0017)	(0.0017)	(0.0016)
Treat × Post	0.0441***	0.0305***	0.0284***
	(0.0032)	(0.0032)	(0.0031)
Property Characteristics	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Distance Measure	Network	Euclidean	Manhattan
Observations	309,876	309,876	309,876
R^2	0.7956	0.7895	0.7906
Adjusted R^2	0.7954	0.7893	0.7905
Residual Std. Error (df = 309614)	0.2637	0.2911	0.2996
F Statistic (df = 261; 309614)	4,617.6720***	4,449.7340***	4,479.8210***

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 9: Inverse Probability Weighted DID

7.3 Clustered Standard Errors

Clustered standard errors are omitted from the main specifications due to the empirically defined treatment zones based on distance-based hedonic modelling (Figure 5), which create concentrated and overlapping spatial units. This violates the assumption of independent, numerous clusters. Significant spatial lag in the SDID model further confirms interdependence in housing prices, suggesting that clustering may distort the true error structure. Given these issues, and the inclusion of detailed spatial and temporal fixed effects, robust standard errors provide a more appropriate basis for inference. Table 10 presents clustered standard errors as a sensitivity check. While announcement and post-opening effects weaken, the construction phase effect remains strongly significant, reinforcing the core finding that LVU is strongest during construction.

	(1)	(2)	(3)
Treat × Announcement	0.0315	0.0285	0.0221
	(0.0215)	(0.0210)	(0.0185)
Treat × Construction	0.0531***	0.0347***	0.0286***
	(0.0149)	(0.0105)	(0.0095)
Treat × Post	0.0301**	0.0103	0.0081
	(0.0130)	(0.0101)	(0.0101)
Property Characteristics	Yes	Yes	Yes
Neighbourhood Attributes	Yes	Yes	Yes
Spatial Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes
Distance Measure	Network	Euclidean	Manhattan
Observations	309,876	309,876	309,876
R^2	0.7995	0.7991	0.7991
Within R^2	0.5823	0.5815	0.5813

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 10: Clustered Standard Errors

8 Discussion

8.1 Cost-Benefit Analysis

Capitalisation effects during construction from Table 2 based on network distance states that residential properties near an Elizabeth line station experienced, on average, uplift of 5.31%. Given that the average housing value within the treatment group is £481,896, this implies an average LVU of £25,589. Since there are 120,331 residential properties in the treatment group, the total LVU resulting from the Elizabeth line amounts to £3.08 billion. With an estimated final cost of £18.9 billion, this represents approximately 16.3% of total costs. Of course the total LVU will of course vary depending on which distance measure and phase's estimates one chooses to apply, and a more refined analysis would involve a station-by-station analysis. Nevertheless, the bottom line is that the aggregate windfall gains arising from accessibility improvements reflects a non-trivial proportion of the line's construction costs.

8.2 Relative Beneficiaries

Despite the aggregate benefits derived from the Elizabeth line, these gains do not necessarily benefit everyone, nor are they universally distributed. Although the taxpayer bears a cost, the net gain or loss one experiences will depend on to what extent the line directly or indirectly benefits them. Non-users who do not experience any indirect benefits will bear the greatest burden — most likely those living particularly far from the line.

As we have seen, even for homeowners within the treatment zone, windfall gains are not homogenous. In general, properties within 0–900m of stations, and those in Central London, East of London or Canary Wharf experience above-average LVU. Given that UK median annual earnings in 2023–24 were £37,430, the average windfall gain represents around 68% of the median person's yearly income. Within areas facing higher capitalisation effects, LVU will easily exceed 100%. As wealthier individuals are more likely to be homeowners (Gregg & Kanabar, 2023), such a result would indicate that, all else equal, the line exacerbates wealth inequality via the LVU channel. If rents were to rise in response to the line, as suggested by CBRE (2024), this would represent an additional redistribution of resources from tenants to landlords, exacerbating income inequality. Again, wealth disparities will be unevenly concentrated across regions, with Central London, East London and East generating more wealth than other Elizabeth-line areas. While one could argue that East London should accumulate more wealth due to its greater deprivation, the reality, as shown by Canary Wharf, is that such wealth creation is concentrated within a select few stations.

It is important to note, however, that these results must be contextualised with the broader socioeconomic and environmental benefits beyond LVU provided by the Elizabeth line. The line helps connect previously underserved communities in East and South East London to the city centre, and in the process, stimulates local economies and offers easier access to opportunities and resources elsewhere. While property-driven wealth inequalities may arise, they must not overshadow the overarching benefits and goal of regional development.

8.3 Land Value Capture

The prior discussion presents a clear case for capturing some of these windfall gains. While designing a perfect LVC mechanism goes beyond the scope of this paper, it is worth discussing the current state of affairs. The UK currently has four property taxes: Council Tax, Business Rates, Stamp Duty Land Tax and Capital Gains Tax. However, all four are ineffective at capturing LVU because they are relatively unresponsive to changes in property values (Transport for London, 2017). London, however, has already used a levy on commercial property, the Business Rates Supplement, which helped raise £4.1 billion specifically towards Crossrail; the Community Infrastructure Levy, a charge imposed on new developments, and developer contributions each raised an additional £300 million (Buck, 2017).

Hong Kong's "Rail + Property" model offers a celebrated example of successful LVC, whereby the Mass Transit Railway Corporation obtains development rights for land around new stations at pre-rail values, and uses post-rail values to recoup its costs, generating over half of the operator's total income (Cervero & Murakami, 2009). However, transposing this model to the UK would be challenging, as Hong Kong has a public leasehold system, empowering them to easily grant long-term leases. TfL (2017) have proposed several potential LVC methods. This includes Community Infrastructure Levy and Section 106 requirements for new developments near major transport projects to help capture uplift without directly taxing homeowners. Additionally, allowing a portion of Stamp Duty Land Tax growth in transport-enhanced areas to be reinvested locally would provide a steady revenue stream without imposing new levies. Political opposition and disputes over taxes based on property valuations will inevitably rise against these measures if executed, paralleling some of the demerits of a land value tax, a measure proposed since the late 19th century, but never implemented in the UK. Nonetheless, a hybrid strategy that leverages these mechanisms could help London systematically capture the value it creates, ensuring future transport projects are more self-sustaining.

9 Conclusion

Using DID to identify the effects of the Elizabeth line on residential property prices across its lifespan, the findings show that the line has increased housing values for those within the treatment zone, with the models satisfying the parallel trends assumption and are robust against using propensity score weighting and clustered standard errors. Although the average capitalisation effects are valued at 3.15%, 5.31% and 3.01% for the announcement, construction and operational phases respectively, it is ultimately the location and timing of transactions that matter most. The largest uplift is typically experienced towards the end of the construction phase, followed by announcement and opening. Properties within 900m of stations and those near interchange stations with zero or at least two connecting lines typically experience above-average LVU compared to those for the entire dataset.

The network distance measure yields the highest estimates, and despite its conceptual advantage, there is little evidence supporting the notion that the Manhattan distance is systematically better than the Euclidean distance measure in approximating network distance results, highlighting their unique and distinct properties. Lastly, the SDID models yield lower LVU estimates than aspatial DID models, provide a better fit and suggest that positive spillover effects may exist. With an estimated aggregate LVU of £3.08 billion, or 16.3% of the Elizabeth line's total construction costs, there is strong reason to implement LVC mechanisms on residential properties experiencing uplift, both in the rental and sales market.

LVU is merely one of the many benefits provided by the Elizabeth line, and the full impact of such a large and anticipated transport line will almost certainly cover its total cost multiple times over. Therefore, exploring capitalisation effects of other major upcoming transport projects — most notably High Speed 2 — will deepen our understanding of LVU dynamics in the UK, providing crucial evidence for decision-makers to invest in infrastructure that will go on to improve and shape the cities we live in.

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