Impact of local public transport schemes on economic growth

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Abstract

This paper evaluates the economic impacts of local public transport schemes - small additions to the transport network - focusing on effects on the number of businesses, employment, turnover, productivity, and house prices. Using granular data from 1997 to 2019 and quasi-experimental methods, we provide new evidence on the local economic consequences of these interventions. Our preliminary results show that although the number of businesses increases, there is no effect on total employment, and we observe a negative effect in median turnover and a small reduction in median employment. These patterns are consistent with a shift in the composition of firms: the number of micro-businesses (fewer than 10 employees) rises, and because such firms typically generate lower turnover, this helps explain the observed declines in other outcomes. The impacts also appear highly localised, with no evidence of effects beyond 0.5 km. In the next stage of the analysis, we will explore these mechanisms in more detail and examine whether impacts differ by type of transport scheme (trams, buses, and accessibility projects).

Keywords: Transport, employment.

JEL codes: R12, L25.

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1. Introduction

In 2019, total spending on transport infrastructure in the UK was over £20 billion.[1] In addition to direct user benefits, this spending generates wider economic benefits. Transport infrastructure increases economic activity by reducing costs for businesses and commuters, improving market access, and facilitating agglomeration economies. However, while the effect of overall infrastructure on total economic activity is expected to be positive, the economic impacts of local schemes are uncertain as schemes may be relatively small, the local economic impacts are not necessarily positive – infrastructure improvements increase competition as well as allowing local businesses to relocate and serve local markets from afar – and impacts may not be evenly spread across space.

In the UK, wider economic benefits are included in ex-ante appraisal following national guidance. This leaves open the question of whether these benefits are realised. The aim of this paper is to evaluate the local economic impact of public transport schemes on the number of firms, employment, turnover, productivity, and house prices. We use data for 16 Local Major schemes that were (partly) funded by the Department for Transport (DfT) and implemented between 2010 and 2017. A key objective is to assess whether these schemes generated spillover effects or displacement effects in nearby areas.

This preliminary version outlines the public transport schemes under evaluation (Section 2), the empirical strategy and identification approach (Section 3), the data (Section 4), the preliminary results (Section 5), and final remarks and next steps for the research (Section 6).

2. Public transport schemes under evaluation

The public transport schemes under evaluation are part of the Local Majors, capital schemes costing more than £5 million, approved between 2007 and 2018 and promoted and delivered by local government or the Highways Agency. Total spending on Local Majors between 2007 and 2019 was £5bn, a small component of overall UK

[1] Source: Transport infrastructure investment and maintenance spending, OECD. (https://stats.oecd.org/Index.aspx?DataSetCode=ITF_INV-MTN_DATA – accessed on 06/03/2023).

spending of £187bn in the same time period – something which is likely to be true for most evaluations of local schemes.[2] The schemes are of local or regional, rather than national, importance – hence we evaluate the economic impact of local schemes and isolate this from the impact of other investment in the transport network. The schemes are funded by central and local government, with central government providing most of the funding – between 75 and 90 percent depending on the type of scheme.[3]

DfT provided information on the characteristics of schemes (year of opening, type of scheme, cost), but not the exact location. Reports and businesses cases provided by local authorities, show that most of the schemes were built to improve connectivity. A small number of schemes mention increasing productivity, employment, businesses, or wages as an objective. In total, there are 16 transport schemes. The schemes are spatially spread out, with the majority located in northern England. Figure 1 maps the schemes.

The average construction time of all public transport schemes is 33 months. The 16 public transport schemes used in the analysis comprise seven bus corridor schemes, five tram schemes, and four accessibility schemes, which improve the accessibility of existing stations. These are relatively small schemes compared to those usually evaluated in the literature. For example, the Jubilee Line extension, evaluated by Gibbons and Machin (2005) using a distance-based approach, cost £3.5 billion and took six years to build. Although, many existing evaluations focus on these larger schemes, local schemes more commonly involve investment in smaller projects such as the schemes we are evaluating.

Although funding details and objectives may vary across schemes, the nature of the information available for a typical evaluation of local schemes is likely to be similar – we have a list of funded schemes, constructed over a relatively short period, with little detail on how decisions were made or which other projects were considered, but not funded. Our schemes are only a part of overall investment – highlighting the importance

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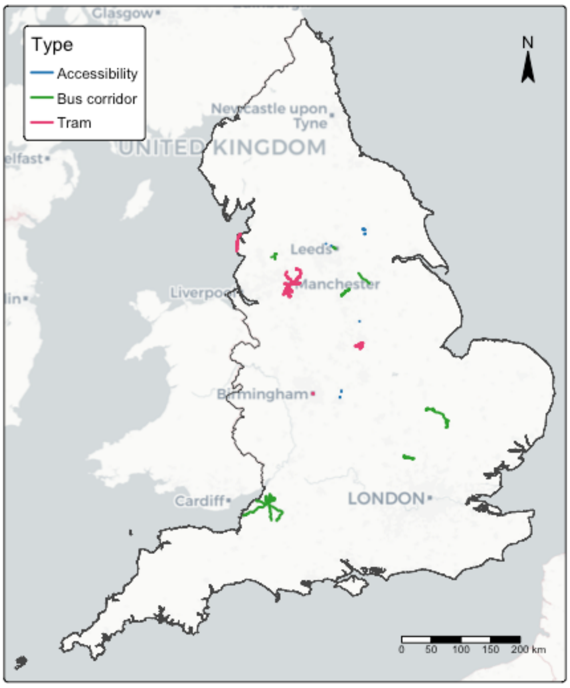
[2] See data from OECD: Transport infrastructure investment and maintenance (oecd.org) accessed 04/10/2023.

[3] See National Audit Office (2011) for more details on the schemes including programme management and the process for evaluation of direct user benefits. https://www.nao.org.uk/wp-content/uploads/2011/05/Local_Authority_major_capital_schemes.pdf

of using evaluation methods that allow separation of the impact of individual schemes from other investments.

Figure 1. Map of public transport schemes



Notes: The figure shows public transport schemes across England, with each type represented by a distinct colour.

3. Empirical Strategy and identification

For schemes where the impacts are expected to be concentrated in a limited number of areas close to the scheme and if these areas can be identified from details of the scheme – for example, around stations on a new subway line – treatment and control groups can be constructed based on distance to the scheme. This approach deals with the problem of selection on observables by using data on observable characteristics, time-invariant unobservables by using fixed effects, and time-varying observables by using similar areas that are close, but not too close, to the scheme. This relies on the principle that nearby areas tend to be similar – so areas close to a scheme, but not too close, might provide an estimate of what would have happened in the absence of the scheme.

The requirement that the control areas cannot be too close is because they need to be unaffected by the scheme. The assumption that treatment is limited to areas close to the scheme is reasonable when households or businesses located in those areas are likely to benefit most – either because of improved accessibility to other locations or because, for customer-facing businesses, the scheme increases customers.[4] Distance from the scheme can also approximate variation in the intensity of treatment assuming that the strength of these effects depends on distance to the scheme. These assumptions make sense for public transport schemes which depend on people walking to access the scheme.

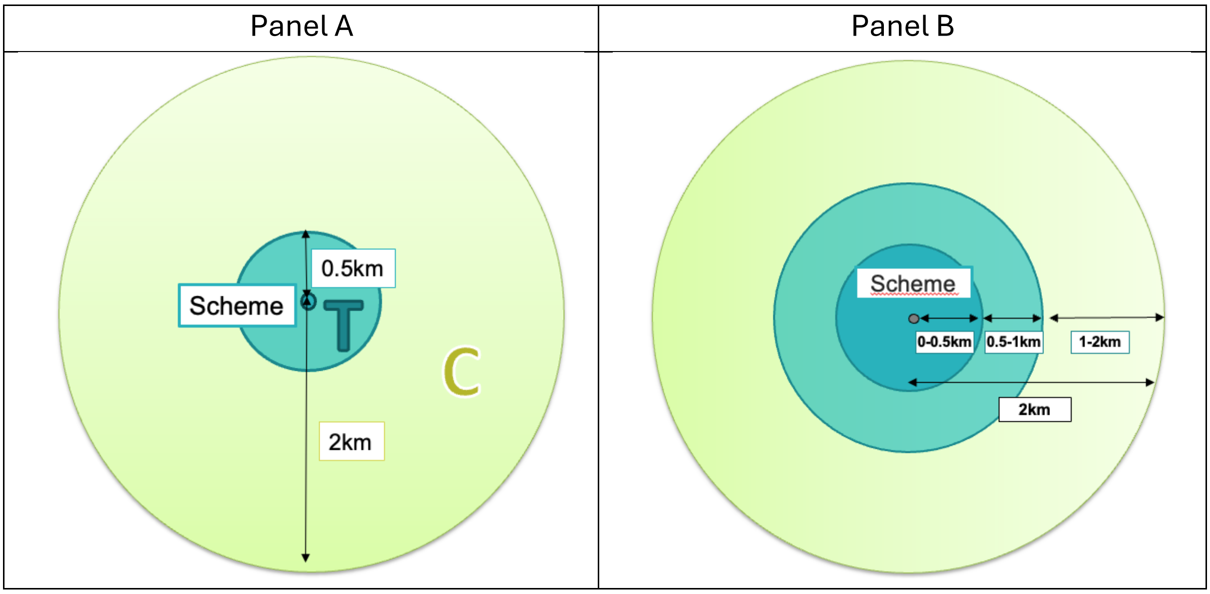
Implementation of distance-based approaches usually involves choosing distance thresholds to define treatment and control groups.[5] For example, as illustrated in Panel A of Figure 2 an evaluation could assume that all areas within 0.5 kilometres of a new bus station are treated (labelled as T) and that areas between 0.5 and 2 kilometres from the station are similar, but untreated and suitable as control areas (labelled as C). Comparing change in outcomes in T-areas to change in outcomes in C-areas gives the impact of the bus station providing that changes in T-areas and C-areas would have been similar in the absence of the scheme. For the treated group, the threshold distance to the scheme should ideally be chosen to include all affected areas while excluding areas that are unaffected. To guide decisions, evaluations can use additional data or assumptions on how users of distinct types of schemes behave (such as how far people are willing to walk to use a station). Robustness checks can use different thresholds to see if results change.

A similar process can be used to establish the distance threshold that defines areas in the control group which should be 'near enough' to be similar to the treated group, without being affected by the scheme. Data on area characteristics can help inform this decision and can be used to refine estimates as discussed above. The choice of threshold will also determine whether nearby areas are similar enough to control for time-varying unobservable characteristics – something which cannot be checked directly. One option is to compare pre-trends in economic outcomes for the two groups before the scheme is built assuming that similar trends mean unobservables were similar pre-scheme and will continue to be similar post-scheme opening. While this

[4] This assumption is supported by evidence on business outcomes and house prices as discussed in What Works Growth evidence review on transport infrastructure and rapid evidence review on rail investment.
[5] It also requires schemes and areas to be geo-located. The way in which this is done depends on the nature of the schemes and area data. We discuss how we do this for Local Majors below.

provides some re-assurance that the two groups are comparable it does not guarantee the control group is unaffected by the scheme. To account for this, as with the threshold for treated groups, robustness checks can use different thresholds to see if results change.

Figure 2. An illustration of using distance-based approaches to define treatment and control groups and to allow for variation in the intensity of treatment.



A further advantage of the distance-based approach is that distance to the scheme can be used to proxy for intensity of treatment. In this refinement, treatment and control groups are defined as above. Rather than assume effects are a linear function of distance, it is common to define multiple distance bands within the treated group to allow for non-linearity in how distance affects intensity. For example, returning to the example in Figure 2, Panel B shows bands of treated areas within 0-0.5km, 0.5-1km and which can be compared to control areas 1-2km away. We might expect the intensity of treatment and the impact of the scheme to be greatest in the closest band, but the use of bands does not impose this assumption (whereas modelling the intensity of treatment as a linear function of distance would). This flexibility comes at a cost because it reduces the number of areas in each band and hence the precision of the estimates. Having more observations provides more information (variations in treatment and outcome variables), which makes it easier to separate the impact of the scheme from random variation.[6]

[6] This is also an issue for the robustness check, discussed earlier, that varies the width of bands.

Defining multiple treatment bands also helps check for displacement – when areas that benefit from an increase in business activity do so at the expense of other areas. This is a particular concern for distance-based methodologies because displacement may be more likely from control group areas that are close, but not very close to the scheme. If the control group is negatively affected, then the impact of the scheme will be overestimated. In principle, this approach could be used to estimate the impact of each scheme, but in practice most local schemes – including those funded through Local Majors – only affect a relatively small number of areas, limiting the number of data points, meaning estimates are imprecise. By pooling across all schemes, the coefficient captures the average impact of all schemes. This is the approach we follow.

More formally, when using a single treatment and control group (that is, generalising Panel A of Figure 2) and data on multiple schemes the estimating equation is:

$$Y_{it} = \alpha_i + \eta_t + \gamma_{rt} + \beta(T_i \times Post_t) + \varepsilon_{it} \tag{1}$$

where:

- Y_{it} is the outcome (for example, employment) for area i at time t.
- α_i are area fixed effects, which control for all time-invariant unobserved characteristics of each area (for example, the presence of long-standing area congestion).[7]
- η_t are year fixed effects, which capture shocks to the economy at time *t* that are common to all areas (for example, a national economic downturn).
- γ_{rt} are scheme-by-year fixed effects, which capture shocks common to all areas surrounding scheme *r* at time *t* (for example, a local factory closes).
- T_i is a binary treatment variable defined based on distance to the scheme.
- $Post_t$ is a binary indicator taking value one at time *t* if the scheme is open.
- ε_{it} is an idiosyncratic error term, which captures all other factors that determine outcome Y_{it}.

When the opening date varies across schemes – as it does for Local Majors – time t is normalised to be zero at the date of opening. β is the coefficient of interest capturing the average local impact of the public transport investments on outcomes conditional on the fixed effects (or the percentage change if the outcome variable is defined in

[7] Including the area dummies means estimation uses variations from the mean for each area. Conceptually, these play the same role as time-differencing in two period settings by controlling for time-invariant unobservable characteristics that affect outcomes and scheme placement.

logs). When introducing several distance bands (that is, generalising Figure 2, Panel B), the estimating equation is:

$$Y_{it} = \alpha_i + \eta_t + \gamma_{rt} + \sum_{d=1}^{D} \beta_{id} T_{id} \times Post_{it} + \varepsilon_{it} \tag{2}$$

With the only change being the introduction of several indicators, T_{id}, equal to one when the distance to the scheme is *d*-1 to *d*. For example, in Figure 2, Panel B, T_{i1} is equal to one when area *i* is within 0-0.5km of the scheme, T_{i2} is equal to one when it is within 0.5-1km of the scheme.

The identifying assumption is that the variation in distance to public transport among units close to each scheme is exogenous. By focusing on rings, the induced changes in connectivity are uncorrelated with the unobservable determinants of the outcomes, conditional on controlling for the fixed effects described above. We refer to this as randomness at small scales. This assumption is supported by the type of public transport schemes under study and their objectives – bus corridors, trams, and improved accessibility to existing stations, which aim to improve the transport system, rather than economic outcomes in a particular location.[8]

These distance-based methodologies have been widely used in the evaluation of public transport schemes. We use them for 16 of the Local Major schemes that involve suitable public transport investments. As always, the details of implementation depend on the available data, which we describe in the next section.

4. Data

To evaluate the impact of transport schemes at small spatial scales using the methods developed above requires information on schemes and outcomes of interest for a suitable geography. Calculation of distances requires schemes to be geo-located. Data on Local Major schemes was provided by DfT. This included information on the timeline of projects (i.e., date of approval, date construction started and date of opening). DfT could not provide geo-coordinates of schemes (i.e., shapefiles of the

[8] We are not arguing that scheme location is exogenous, but that the variation in distance to public transport among units close to each scheme is exogenous. For example, this assumption would hold if, as is likely in practice, the placing of stops is driven by the availability of suitable stopping points, requirements on spacing between stops, etc. rather than by changes in local employment.

schemes). We used information from the scheme reports provided by DfT i.e. maps, building plans, and figures to geo-locate the infrastructure and create shapefiles of the schemes.

For firm outcomes, we use data from the Office for National Statistics (ONS) Business Structure Database (BSD) accessed through the Secure Research Services (SRS). The BSD includes a yearly snapshot of UK businesses that registered for either VAT or PAYE. We focus on 1997 to 2019 (dropping 2020 data given the Covid-19 pandemic). BSD includes data on sector of production (5-digit Standard Industrial Classification (SIC)) and employment for Local Units (LU) – which should be the smallest unit that makes sense for the firm (for example, a branch). Information on turnover is for Reporting Units (RUs) which can comprise more than one LU. An enterprise may choose to report data for multiple RUs. For example, a supermarket chain might use regional RUs comprising all outlets (LUs) within a given region. We assign turnover to LUs based on employment shares.

We focus on five firm outcomes: total number of businesses, total employment, average employment within businesses, average turnover, and average labour productivity (defined at the firm level as turnover divided by the number of employees).

For house price data, we use data from the Land Registry Price Paid data + EPC for the period 1995 to 2019, which covers almost all residential transactions in England and Wales. This dataset includes the transaction price, postcode, dwelling type (detached, semi-detached, terrace or flat), contract type (freehold or leasehold), and if the property is a new build. We exclude all transactions with missing location data.

5. Preliminary results

We evaluate 16 public transport schemes using distance-based treatment definitions. The main empirical challenges relate to the availability of suitable outcome data and the limited number of affected areas, which may reduce the precision of estimated effects—especially when comparing different types of schemes. An Output Area (OA) *i* is considered treated ($T_i = 1$) when the distance from its centroid to the nearest part of the scheme is 0–0.5 km. Control OAs ($T_i = 0$) are those with centroids located 0.5–2 km away. To examine potential displacement effects, we implement a spatial differencing strategy as in equation (2), replacing T_i in equation (1) with indicators for 0.5-km distance bands. Specifically, wards 1–2 km from the scheme serve as controls, while we differentiate treated wards in the 0–0.5 km and 0.5–1 km bands. This allows us to identify effects in close proximity to the schemes and assess whether positive impacts come at the expense of neighbouring areas.

Table 1. Public transport schemes

	No. of firms	**Median turnover**	**Median employment**	**Median productivity**	**Median House prices**
0-0.5 km ring	3.68**	-3.04**	-3.15*	-0.59	1.66*
	(1.33)	(1.12)	(1.75)	(0.82)	(0.88)
Observations	166,781	166,781	166,781	166,781	160,178
Year FE	Yes	Yes	Yes	Yes	Yes
OA FE	Yes	Yes	Yes	Yes	Yes
Scheme-by-year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the scheme level. Number of clusters: 16. The dependent variables are the natural logarithm of outcomes. Coefficients are multiplied by 100 to ease their interpretation (as percentage changes directly).

Table 1 shows preliminary estimates from the rings approach, which considers a single 0–0.5 km treatment ring. We examine the number of firms and median turnover, employment, productivity, and house prices. The number of firms increases by approximately 3.7%, indicating that the schemes attract additional businesses in areas closest to the intervention. However, median turnover and employment both decline by roughly 3%, while the effect on productivity is statistically insignificant. We find that the effect on total employment is not significant. These patterns suggest that although more firms enter the area, the median firm becomes smaller, with no associated productivity improvement. By contrast, house prices rise by about 1.66%, consistent with improved transport accessibility being capitalised into local property values. All specifications include year, output area, and scheme-by-year fixed effects, and each regression uses approximately 166,000 observations.

We next decompose the effects by firm size - micro (fewer than 10 employees), small (10–49), medium (50–249), and large (250+). This helps assess whether the 3.68% increase in firm counts reflects changes in the composition of firms. Table 2 shows that the increase is driven almost entirely by micro firms, which rise by about 5.45%. Effects for small, medium, and large firms are not statistically significant. These results suggest that the schemes primarily attract very small businesses, rather than larger or more established firms.

Table 2. Rings – Effects by firm size

	No. of firms	**Micro firms**	**Small firms**	**Medium firms**	**Large firms**
0-0.5 km ring	3.68**	5.45***	2.17	2.09	0.67
	(1.33)	(0.96)	(1.49)	(2.36)	(2.50)
Observations	166,781	166,781	166,781	166,781	166,781
Year FE	Yes	Yes	Yes	Yes	Yes
OA FE	Yes	Yes	Yes	Yes	Yes
Scheme-by-year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the scheme level. Number of clusters: 16. The dependent variables are the natural logarithm of outcomes. Coefficients are multiplied by 100 to ease their interpretation (as percentage changes directly).

Turning to the bands approach, we again observe highly localised effects. In the 0–0.5 km band, the number of firms increases by around 4.2%, while median turnover declines by about 3.6%. Other outcomes show no significant effects. In the 0.5–1 km band, coefficients are small and statistically insignificant across all firm-level outcomes. These results reinforce the conclusion that firm responses are concentrated very close to the schemes: they appear to encourage business entry within 500 metres, but the typical firm becomes smaller and we find no evidence of productivity improvements, spillovers, or displacement. For house prices, however, the pattern differs: the 0–0.5 km band shows positive effects, and the 0.5–1 km band exhibits significant positive spillovers, consistent with wider capitalisation effects in the housing market.

Finally, we examine firm-size-specific effects in the bands approach. Within 0–0.5 km, micro firms increase by roughly 4.6%, while effects for small, medium, and large firms remain statistically insignificant. In the 0.5–1 km band, none of the estimates are significant. These results again suggest that the schemes primarily attract micro firms, pointing to an influx of very small businesses rather than growth among larger firms. Further work is ongoing to understand the mechanisms driving these patterns.

Table 3. Bands – Effects of schemes on economic outcomes

	No. of firms	**Median turnover**	**Median employment**	**Median productivity**	**Median House prices**
0-0.5 km band	4.18**	-3.61**	-3.67	-0.51	2.38**
	(1.55)	(1.58)	(2.14)	(0.863)	(0.92)
0.5-1 km band	1.23	-1.40	-1.27	0.199	1.77***
	(1.32)	(1.96)	(1.49)	(1.13)	(0.55)
Observations	166,781	166,781	166,781	166,781	160,178
Year FE	Yes	Yes	Yes	Yes	Yes
OA FE	Yes	Yes	Yes	Yes	Yes
Scheme-by-year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the scheme level. Number of clusters: 16. The dependent variables are the natural logarithm of outcomes. Coefficients are multiplied by 100 to ease their interpretation (as percentage changes directly).

Table 4. Bands – Effects by firm size

	No. of firms	**Micro firms**	**Small firms**	**Medium firms**	**Large firms**
0-0.5 km band	4.18**	4.63**	1.94	0.77	3.01
	(1.55)	(1.74)	(1.90)	(2.55)	(3.41)
0.5-1 km band	1.23	1.40	-0.544	-3.00	4.81
	(1.32)	(1.57)	(1.75)	(1.76)	(4.30)
Observations	166,781	166,781	166,781	166,781	166,781
Year FE	Yes	Yes	Yes	Yes	Yes
OA FE	Yes	Yes	Yes	Yes	Yes
Scheme-by-year FE	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the scheme level. Number of clusters: 16. The dependent variables are the natural logarithm of outcomes. Coefficients are multiplied by 100 to ease their interpretation (as percentage changes directly).

6. Final remarks and next steps

Transport infrastructure investment can generate wider economic benefits in addition to direct user benefits. For public transport schemes, our difference-in-differences strategy combined with a distance-based identification approach reveals several localised impacts on economic outcomes. Effects are concentrated within approximately 0.5 km of the schemes. We find positive effects on the number of businesses but no impact on overall employment, alongside negative effects on median turnover and a small decline in median employment. These patterns can be reconciled by a shift in the composition of firms: the number of micro-businesses (fewer than 10 employees) increases, and because these firms typically have lower turnover, the observed decline in median turnover is unsurprising. Another potential mechanism is increased competition, which may reduce turnover for both new entrants and incumbent firms—an explanation we are currently investigating. Finally, we find that house prices increase up to 1 km from a scheme, which likely reflects increased demand for housing rather than a reduction in supply.

Our next steps focus on understanding the heterogeneity behind these results. First, we will assess whether effects are driven by specific types of schemes—for instance, whether accessibility improvements, tram investments, or bus-focused upgrades have stronger impacts. We will then explore the firm-level dynamics in more depth: which sectors respond most strongly, and to what extent we are capturing changes among established firms, new entrants, or relocating firms. This will shed light on potential relocation mechanisms. On the housing side, we will investigate whether different property types respond differently to the schemes. Finally, we will conduct a comprehensive set of robustness checks, including alternative ring sizes, controls for staggered openings, and estimation at the LSOA level, to ensure that our findings are robust.

References

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