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Assessing agglomeration impacts of large-scale transport infrastructure

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ABSTRACT

Large-scale transport infrastructure can influence national patterns of population and employment, and induce agglomeration effects and long-term economic development. However, conventional appraisal methods often do not capture these indirect impacts. This study investigates how transport investments may affect the spatial distribution of population and employment and the resulting agglomeration effects and productivity changes, using East West Rail in England as a case study. We develop an extended land use–transport interaction (LUTI) model with industry-level disaggregation. It integrates a recursive gravity framework with a multimodal transport network and iteratively updates residential and employment distributions in response to accessibility changes. Results reveal that the rail line stimulates significant growth within the region, particularly along its route, but attracts limited inflows from more distant areas. Employment relocation (particularly in retail and service sectors) responds more sensitively to accessibility gains than residential patterns. When we apply our model to the national level (England and Wales), we capture the net benefits of agglomeration and disagglomeration. We find significant productivity gains in the corridor, with an estimated uplift of about 0.7%, and a modest but positive impact at the national scale around 0.02%. The results suggest that part of the corridor-level gain reflects redistribution through displacement from elsewhere rather than wholly additional national output. The analysis can thus contribute to the understanding of granular spatial patterns related to agglomeration and disagglomeration that arise from transport investments.

1. Introduction

Transport infrastructure can contribute to economic growth by reducing travel costs, creating and relocating jobs, changing proximity to enhance agglomeration effects, encouraging private investment and strengthening labour markets (Laird and Venables, 2017). These impacts are often more significant in large-scale, cross-regional projects, which require long-term commitment and investments. However, traditional assessment techniques like Cost-Benefit Analysis (CBA) do not capture impacts arising from land use changes and relocation such as agglomeration impacts (Laird et al., 2014; Börjesson et al., 2014). Due to CBA's assumption of perfect competition in markets, prices are assumed to reflect all relevant costs and benefits (Wangsness et al., 2017). This assumption abstracts from real-world market distortions such as externalities and increasing returns to scale, which can cause transport investments to generate indirect impacts that go beyond direct user benefits (Graham and Gibbons, 2019; Department for Transport, 2020). These indirect impacts are referred to as Wider Economic Impacts (WEIs), which may arise from factors such as market failures, distortions and agglomeration-related productivity effects, and can make up a significant proportion of the benefits in transport appraisals. For instance, in the United Kingdom, WEIs can account for more than 20 percent of total benefits in cost benefit analysis, and around 30 to 40 percent of the benefits from generalised cost savings for major rail projects such as High Speed 2 (HS2), a planned high-speed rail line between London and northern England (Department for Transport, 2012; Rothengatter, 2017). At the same time, for large-scale transport projects, part of the observed impacts may reflect displacement with limited net national effects, while still being highly relevant for local policy decisions. Therefore, there is growing demand for governments and local authorities to adopt modelling approaches that can capture WEIs more effectively through their interdependencies and dynamic system behaviour (International Transport Forum, 2020; Department for Transport, 2019a). Land use and transport interaction (LUTI) models are one example.

LUTI models have evolved for over five decades and have been routinely applied in practice. They simulate interactions between land use and transport systems for spatial development based on foundations from microeconomics such as random utility theory and bid rent theory (Van Wee, 2015; Acheampong and Silva, 2015). LUTI models often

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assume an urban equilibrium in which the distributions of population and employment are mutually dependent, as formalised in the Lowry model through feedback between service employment location and the residential location of service employees (Lowry, 1964). However, in practice this equilibrium condition is often overlooked. Many models simulate employment or population independently and thereby neglect their interdependence. While some more advanced models, such as TRANUS (De La Barra et al., 1984), incorporate direct bidirectional feedback where employment drives population allocation and population size in turn influences employment distribution through iterative location-choice mechanisms, their computational complexity often limits their scalability for large urban systems. This highlights the need for LUTI models that capture key feedbacks while remaining computationally tractable. On the one hand, capturing feedback mechanisms such as how residential location responds to employment distribution, and how employment adjusts in response to population changes, can help modellers better understand the interactions among different components of the urban system. On the other hand, increasing data availability and computational capacity have opened up new opportunities for more realistic assessment, especially for large scale projects.

This study uses East West Rail in England to examine how a large-scale transport investment may redistribute population and employment and thus give rise to productivity changes at the regional and national scales. To do so, we: (1) introduce a national-scale recursive LUTI model that puts the equilibrium between employment and population into practical use; (2) show how enhanced accessibility strengthens existing agglomeration centres, redistributes activity within the corridor and displaces activity elsewhere; and (3) link these spatial shifts to agglomeration effects, distinguishing local gains from net national additionality.

2. Wider economic impacts (WEIs), displacement and additionality

In transport appraisal, Cost–Benefit Analysis (CBA) remains the standard method to estimate changes in social welfare, primarily through consumer surplus (Department for Transport, 2023a; Mackie and Nellthorp, 2001; Graham and Gibbons, 2019). However, CBA is not designed to capture wider economic impacts (WEIs) that result from market imperfections and extend beyond direct user benefits (Rothengatter, 2017). Yet, researchers and policymakers agree that estimating WEIs is important when seeking a more comprehensive understanding of the impacts of transport investment (Annema et al., 2007; Vickerman, 2008; Beyazit, 2015).

The concept of WEIs has matured over the past decade, but it has also raised issues and concerns. Two key concerns persist: the significance of WEIs remains contested, and a unified framework for assessing WEIs in transport appraisals has yet to be established (Wangsness et al., 2017; Rothengatter, 2017; Graham and Gibbons, 2019). Specifically, there are ongoing debates on the extent to which WEIs should be included in appraisals and the best ways to account for unintended consequences, such as displacement and disagglomeration (Wangsness et al., 2017; Vickerman, 2024; Laird et al., 2023; Kanemoto, 2013). Although there are concerns that transport investments may exacerbate urban inequality (Beyazit, 2015; Rothengatter, 2017), ex-post analyses often show that WEIs contribute positively to long-term economic growth (Chen and Hall, 2012; Melecky et al., 2019; Beyazit, 2015; Tveter, 2017, 2018; Knowles and Ferbrache, 2016; Du and Zheng, 2020).

The UK is one of the few countries globally to have developed a comprehensive framework for assessing WEIs, as detailed in its Transport Analysis Guidance (TAG A2.1) (Wangsness et al., 2017; Department for Transport, 2020). According to TAG, WEIs should be assessed when market failures and distortions exist or when significant land-use changes are expected. Due to difficulties in integrating WEIs into CBA given inconsistent economic assumptions, the standard approach is to complement CBA with additional economic models, such as LUTI or general equilibrium frameworks (Department for Transport, 2020). In particular, agglomeration effects have become a key consideration in the assessment of transport schemes. This is largely due to the role of transport infrastructure in enabling more concentrated patterns of urban development, which enhance productivity and welfare through external economies of scale at both regional and local levels (Chatman and Noland, 2011; Venables, 2007). Several empirical studies demonstrate that agglomeration effects vary spatially and across industries, reflecting sector-specific spatial patterns and differences in the extent to which each industry relies on transport infrastructure (Song et al., 2012; Holl, 2004; Liu et al., 2022).

Nevertheless, observed productivity gains from improved accessibility may not always represent additional economic output, as they can result from the relocation of existing activities towards more accessible areas (Pogonyi et al., 2018; Department for Transport, 2019b). In other words, local employment or productivity increases may simply reflect displacement rather than an expansion of the national economy. Empirical studies have shown that transport investment can induce displacement (Ángel Garcia-López et al., 2015; Baum-Snow, 2007) while also potentially generating net economic growth through mechanisms such as agglomeration effects (Heblich et al., 2020; Tsivanidis, 2022). Specifically, economic activities may shift between areas with different levels of agglomeration and productivity. When activity moves from less concentrated, lower-productivity areas to more concentrated, higher-productivity areas, agglomeration gains may outweigh losses elsewhere. By contrast, movement towards less agglomerated areas may generate negative effects. Meanwhile, improved accessibility resulting from the transport project may also boost productivity through knowledge spillover (Lee, 2021). This can be referred to as additionality, whereby local economic impacts translate into a net national increase in economic performance after accounting for other effects such as displacement (Department for Transport, 2025a).

3. LUTI modelling: From theory to practice

LUTI models were developed in the 1960s to explore infrastructure investments in motorway systems and address escalating urban planning challenges (Wegener and Fürst, 2004). The Lowry model (1964), widely acknowledged as the first operational LUTI framework, has demonstrated how population and employment patterns could be linked through an economic-base framework, influencing the design of many later LUTI models (Moeckel et al., 2018). Since then, LUTI models have evolved in two distinct directions: one prioritises flexible, complex, and fine-grained modenames,lling on the local scale, while the other leans towards more simplified modelling approaches at regional, national, and global scales (Kii et al., 2016). At the micro scale, utility-based and activity-based models, such as agent-based modelling (ABM), simulate heterogeneous individual location and travel choices and can capture interactions, spatial heterogeneity, and non-linear behaviour (Acheampong and Silva, 2015; Batty, 2011; Miller, 2017). However, more detailed micro-level modelling increases computational and data demands (Acheampong and Silva, 2015).

For large-scale applications, spatial interaction models (SIM) are one of the most representative approaches. They treat space as a discrete system of zones and simulate flows between origins and destinations based on entropy maximisation principles (Acheampong and Silva, 2015; Haynes and Fotheringham, 1984). Models such as QUANT demonstrate that SIM can be implemented at a national scale with thousands of zones, while still retaining relatively fine geographical detail given current data availability and computational power (Batty and Milton, 2021; Lopane et al., 2023, 2025).

The spatial organisation of cities reflects a balance between opposing forces of agglomeration and dispersion (Redding, 2023). According to the New Economic Geography perspective, spatial concentration arises from centripetal forces such as market access, increasing returns, labour pooling and input linkages, whereas centrifugal forces stem from land rents, congestion and other immobile factors that limit further concentration (Krugman, 1998). Improvements in transport connectivity affect this balance by reducing effective commuting frictions and therefore strengthening relative market access across locations. Meanwhile, households and firms may adjust their location choices, leading to a spatial reallocation of residents and employment across connected centres. In the classic monocentric model developed by Alonso (1964), workers trade off commuting costs and housing rents, leading those who live further from the city centre to pay lower rents but incur higher travel costs. This individual trade-off forms the spatial pattern of residential land use in the city. In LUTI models, as in the Lowry model, the location of industrial employment is typically treated as exogenously determined, while the distribution of service employment and population adjusts to reach spatial equilibrium. The demand for services and goods from the population drives changes in the service sector, which in turn affects the need for labour (Moeckel et al., 2020). SIMs provide the formal structure for representing such flows, typically by estimating the volume of movement between origins and destinations based on travel impedance and destination attractiveness. Common variants include unconstrained, singly constrained, and doubly constrained models (Wilson, 1971). A key characteristic of these models is that they capture the behaviour of aggregated demand or supply segments, rather than individual agents or firms (Roy and Thill, 2004). This level of aggregation contributes to the simplicity of the model and facilitates its application at larger spatial scales, although it also introduces the representative agent problem, whereby heterogeneity among individuals may be overlooked (Kemp and Shimomura, 1994).

Previous research on LUTI models has undergone significant theoretical development with a wide range of focus areas. However, in most applied LUTI models either population or employment is specified exogenously, so the theoretical equilibrium between them is not fully achieved in practice. Most implementations remain at the city or regional scale, with limited exploration of national-scale modelling. In addition, the integration of wider economic impacts into LUTI frameworks, especially with industry-level disaggregation, has been explored to a limited extent.

This study addresses these gaps in two ways. First, we develop a recursive LUTI model for England and Wales with employment and population disaggregated by industry. In the model, employment and population adjust jointly, with jobs and residents relocating between zones in response to accessibility changes from the transport model. Second, we convert the modelled changes in employment density into estimates of agglomeration-related productivity effects in different industries. Applied to the East West Rail project, the model shows how improved accessibility changes where jobs and residents locate. It also allows us to assess whether the resulting productivity gains represent a net increase at the national level or mainly reflect a redistribution of existing activity.

4. Methodology

4.1. Case study area

Our case study area is the **Ca**mbridge-**M**ilton **K**eynes-**Ox**ford corridor (CaMKOx) in the UK, identified as a potential "European Silicon Valley" (BBC News, 2025). This corridor is characterised by significant knowledge-intensive activities, hosting world-leading universities and innovation clusters. Over the past two decades, the corridor's economy has grown faster than any region outside London, with the strongest employment growth concentrated in professional and business services and in public services such as education and health, while other service-related sectors have also expanded (MHCLG, 2021). However, growth is thought to be hindered by inadequate transport connectivity and limited housing supply (Barker and Gardiner, 2016). To address these issues, the National Infrastructure Commission has proposed the completion of the East West Rail (EWR) linking Oxford and Cambridge by 2030, alongside the provision of one million new homes and jobs by 2050 (National Infrastructure Commission, 2021). Therefore, the CaMKOx corridor with the planned EWR scheme is a suitable case study for LUTI modelling in this study (see Fig. 1).

4.2. Data

The data used in the model are based on MSOA-level census data in 2011 and are organised into three primary components: commuting flows and travel cost data, origin and destination attributes data, and sector-specific data (see Table 1). Travel cost is measured as generalised journey time (GJT), which comprises the total door-to-door travel duration, including in-vehicle time, waiting times and observed transfer times between modes. England and Wales comprise 7201 zones with 21.6 million flows. Within this, the CaMKOx area includes 426 MSOA zones and 1.14 million travel-to-work flows. The 2011 Population Census is used as it provides a pre-pandemic baseline, capturing typical commuting patterns and enabling robust model calibration prior to the construction of the EWR.

The flow and travel cost dataset comprises a travel-to-work matrix (Office for National Statistics, 2011) that reports origin–destination (OD) flows by travel mode, linking places of residence to workplaces and the modes used to commute. The travel cost matrix is generated using r5py (Fink et al., 2022) with a maximum travel time threshold of two hours and contains travel times in minutes between network-weighted centroids. This 120 min cap is conservative in practice, as UK travel statistics indicate that around 96% of commuters have a usual travel time to work of under 90 min (Department for Transport, 2025b). We use r5py to access the R5 routing engine for computationally efficient national-scale OD matrix calculation. Higgins (2022) reports substantial runtime savings for OD matrix computation when using the same R5 engine via r5r. For example, in a matrix containing 100 million OD pairs, R5r completed the task in under 8 min, whereas other tools, such as ArcGIS Pro, OTP and Emme, required several hours. This motivates our use of r5py to compute a matrix with approximately 52 million OD pairs.

OD pairs farther than two hours are approximated using Euclidean distance. Weighted centroids are applied because the CaMKOx area includes extensive rural zones where a geometric centroid could inaccurately represent travel distances, and they help reduce potential bias in average travel time. We divided the flows into two commuting modes: driving and transit. The driving mode encompasses all car-based travel, including personal driving and taxi services, while the transit mode includes all public transport options, such as rail and bus, as well as individuals who walk to access these services. Active modes are excluded, as they typically occur within single MSOAs and are highly sensitive to centroid location settings, introducing variability that is less relevant to the focus of this study on long-distance travel.

The zonal economic and demographic data describe the characteristics of residential and employment zones. Residential attributes include floorspace, housing prices, and average household income, all derived from the 2011 Census (Office for National Statistics, 2011). Residential floorspace is estimated based on dwelling type and the average floorspace associated with each dwelling type. The employment zone characteristics selected for this study include business floorspace and rateable value for the business floorspace from the Valuation Office Agency (Valuation Office Agency, 2023), as well as Gross Value Added (GVA) for each MSOA zone. GVA is a standard metric used to measure economic activity within a region, encompassing most components of Gross Domestic Product (GDP) excluding product-related taxes and subsidies (Nomis Official Labour Market Statistics, 2023). Prior to selecting these indicators, coefficient significance tests were conducted to confirm their relevance to the locational choices of households. These

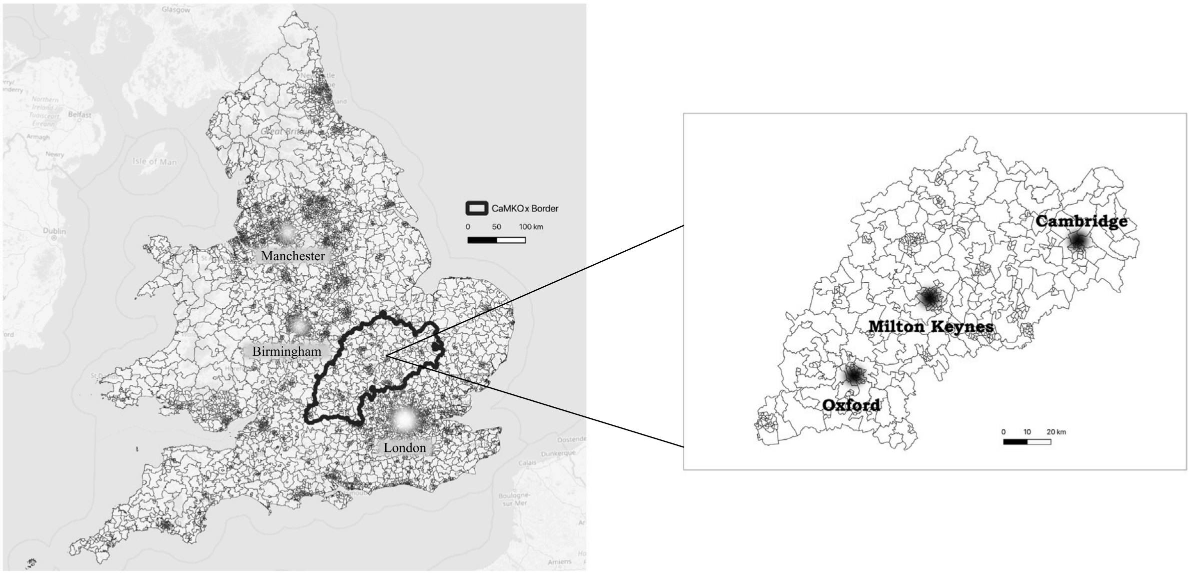


Fig. 1. The Location of the CaMKOx Corridor.

Table 1
Summary statistics for flow and MSOA characteristics.

Data source	Mean	SD	Min	Max
Descriptives for flow matrix				
Total Flows (per O-D pair)	9.14	38.48	0	4998
Flows for Drive (per O-D pair)	6.03	23.02	0	2245
Flows for transit (per O-D pair)	1.63	9.16	0	979
Travel cost for Drive (flow-weighted, minutes)	21.70	23.45	1	455.54
Travel cost for transit (flow-weighted, minutes)	43.45	46.71	1	806.27
Descriptives for characteristics in MSOA as residential				
Total employed population	3705.26	888.24	1344	9012
Residential Floor Space (1000 m^2)	333.28	80.79	135	737
Housing price (GBP/m^2)	2132.81	1828.99	507.81	34 677.90
Average Income (GBP/week)	731.35	190.05	300	1730
Descriptives for characteristics in MSOA as employment				
Total Employees	3668.13	6327.29	465	356 706
Business Floor Space (1000 m^2)	78.72	128.25	1.25	5342
Rateable Value (1000 GBP)	71.25	45.65	9	594
GVA (Million GBP)	182.24	761.37	11.55	52 937.20
Characteristics for Disaggregated industries : Retail/Industrial/Office/Service				
Employment (Mean)	584.66	693.48	997.33	1392.65
Population (Mean)	796.79	947.08	638.04	1323.34
Business Floor Space (1000 m^2) (Mean)	14.13	44.93	12.20	7.45
Rateable Value (1000 GBP) (Mean)	106.28	40.77	85.22	66.64

variables also reflect the economic conditions of land and product markets to some extent.

Sectoral employment and floorspace data are disaggregated into four sectors: office, industrial, retail, and service, and the census employment data are aligned accordingly. In this classification, ‘office’ includes finance-related occupations, ‘industrial’ encompasses manufacturing roles, ‘retail’ also includes sectors such as restaurants and hotels, and ‘service’ refers to community, public, and social sectors such as education, health, and leisure. Within the CaMKOx corridor, employment in office and service industries accounts for over 60% of employment, with a concentration in the northern part of the corridor. In contrast, the retail and industrial sectors are more dispersed. Retail tends to cluster in smaller MSOA areas with higher population densities, while industrial sectors are more common in larger MSOA areas with a higher proportion of agricultural land.

The commuting pattern in CaMKOx shows that 73% of residents live and work within the corridor, while 26% commute to destinations outside it (Fig. 2). Among internal commuters, approximately 73% rely on driving, 19% use active travel modes, and only 8% use public transit. Of these, 6.5% travel by bus and 1.5% by train, suggesting a low use of public transport which may be due to limited accessibility. By contrast, for commuters travelling entirely outside CaMKOx, public transport accounts for 18.5% of trips, more than twice the share within CaMKOx.

Notably, 78% of commuters travel across different MSOAs, implying relatively long commuting distances and a potential demand for improved transit service. Fig. 3 presents the net flows of commuters (employment inflow minus residential outflow), highlighting the functional roles of MSOA zones: positive values indicate residential-dominant areas, while negative values point to zones with higher productivity at work, underscoring the complex economic structure of the region (Redding, 2023). In CaMKOx, workplace zones are predominantly located in city centres such as Oxford, Milton Keynes, and Cambridge. The distribution of the dominant industry in each MSOA (Fig. 4) shows that service industries (in blue) account for the largest share across CaMKOx and are broadly dispersed. This pattern is consistent with the corridor’s higher education and public service base, which includes 11 higher education institutions such as the Universities of Oxford and Cambridge. The office sector (in yellow) is the second

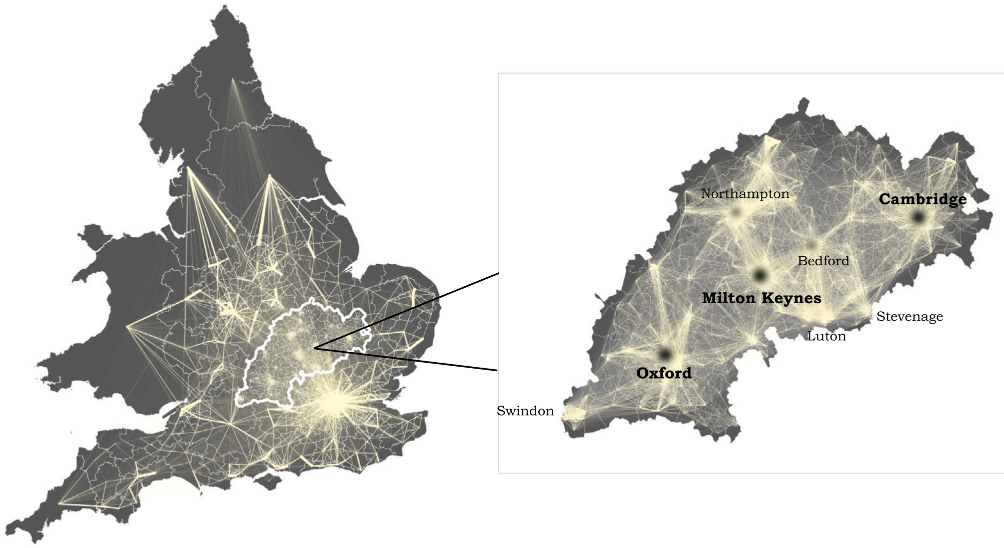


Fig. 2. Flows in England and Wales and CaMKOx.

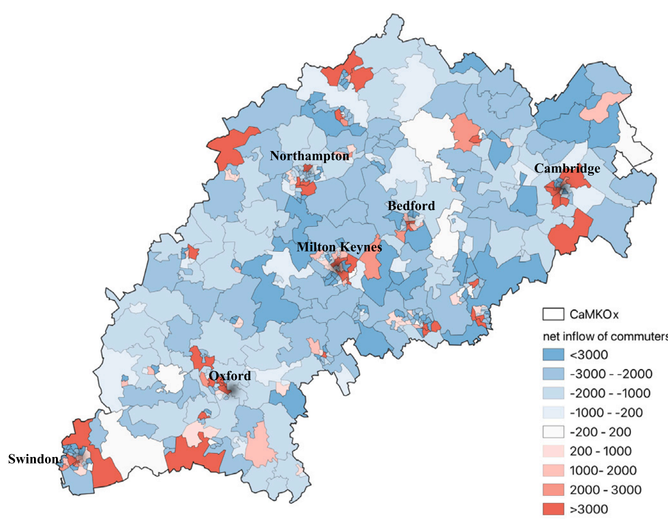


Fig. 3. Net Flows (Inflows and Outflows) in CaMKOx.

most prevalent and is concentrated around city centres, in proximity to knowledge-intensive activities such as the life sciences cluster in Cambridge. Areas dominated by industrial activities (in green) are located mainly in rural MSOAs. By contrast, retail (in red) represents the smallest share and is more concentrated in smaller MSOAs near city centres such as Bicester, underscoring the spatial heterogeneity of local economic structures.

4.3. Recursive LUTI model

Traditional LUTI models usually employ a singly constrained gravity model, as described by Wilson (1971), which can be either production-constrained or attraction-constrained. We refer to these as the population location model and the employment location model respectively in this study. Both models share the same functional form, predicting flows between zones based on either origin or destination characteristics. They can be partially constrained at their origins or destinations and allow a high degree of flexibility in calibration.

In the population location model, T_{ij} represents the number of people residing in zone i and working in zone j. In the employment location model, E_{ji} represents the number of people working in zone j and residing in zone i. In both cases, O_i and D_j refer to the population in zone i and the number of jobs in zone j, respectively; W_j and W_i represent the attractiveness of the destination and origin zones; and α_1, α_2 are parameters controlling sensitivity to attractiveness. $f(C_{ij})$ is a distance decay function, modelled here using a negative exponential form. Other distance-decay forms can be found in the literature, such as an inverse power law, and the choice of functional form affects how quickly interactions attenuate with travel cost, as shown in the empirical study by Reggiani et al. (2011). A_i and B_j are balancing factors ensuring that the origin and destination constraints of the model are satisfied.

$$T_{ij} = A_i O_i W_j^{\alpha_1} f(C_{ij}) \tag{1}$$

$$E_{ji} = B_j D_j W_i^{\alpha_2} f(C_{ji}) \tag{2}$$

We introduce a recursive LUTI model in which two singly constrained gravity models are solved iteratively so that employment and population adjust jointly rather than being fixed on one side. This recursive structure extends the conventional gravity approach by allowing the model to update interdependent variables in successive iterations rather than treating them as externally specified. In doing

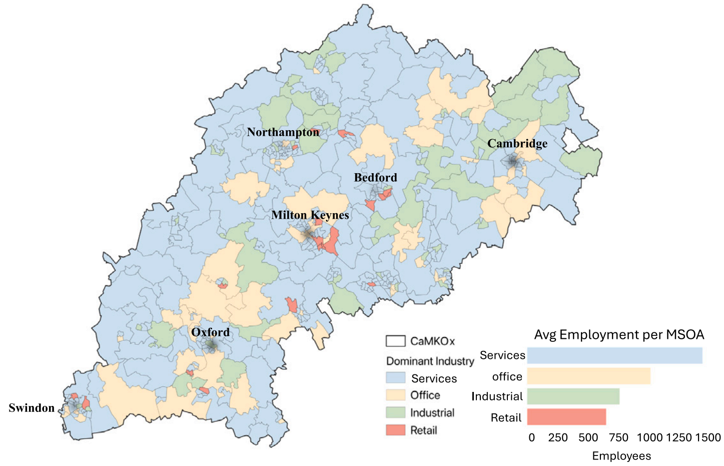


Fig. 4. Dominant industries in CaMKOx.

so, it provides a clearer representation of how changes in accessibility influence the spatial distribution of population and employment (Batty et al., 2024). The framework can be implemented either as an aggregate model, predicting total population and employment, or as a multi-sector model in which employment is disaggregated by industry, depending on the level of detail required for analysing spatial patterns.

The aggregate recursive model begins with the population location model, where the total employment in the origin serves as an exogenous variable for predicting the total population in the destination. As shown in Eq. (3), E_i denotes employment in the origin location i and the variables F_j, I_j, and H_j represent the attraction attributes of residential floorspace, average income, and housing price in the destination j. The distance decay function is defined by the exponential term, where β represents the sensitivity of the flow to travel cost c_{ij} between zones i and j. The parameters l and m represent different industry types and travel modes respectively and τ represents the iteration. In the aggregate model, $l = 1$ represents the total value across all industries, while m takes values $m = 1, 2$, corresponding to driving and transit modes. The driving and transit modes are treated as competing alternatives endogenously in the model. The specific mechanism is shown in Appendix A.2. In the multi-sector model, industries are categorised into four types, denoted by $l = 1, 2, 3, 4$, which represent retail, office, industrial, and service sectors. Each industry type interacts with specific production and attraction variables relevant to its sector.

$$T_{ij}^{l,m}(\tau) = A_i E_i^l F_j^{\alpha_1} I_j^{\alpha_2} H_j^{\alpha_3} \exp(-\beta^{l,m} c_{ij}^m) \tag{3}$$

$$= E_i^l \frac{F_j^{\alpha_1} I_j^{\alpha_2} H_j^{\alpha_3} \exp(-\beta^{l,m} c_{ij}^m)}{\sum_z F_z^{\alpha_1} I_z^{\alpha_2} H_z^{\alpha_3} \exp(-\beta^{l,m} c_{ij}^m)} \tag{4}$$

We could then sum the flows on the origin and destination sides to obtain the predicted employed population P_j:

$$P_j(\tau) = \sum_i^l T_{ij}(\tau) \tag{5}$$

Using the predicted population from the population location model, we then develop the employment location model (Eq. (6)). This model uses predicted population $P_j(\tau)$ as an input to predict the employment flow E_{jk}. It is determined by a balancing factor B_j and attraction attributes such as business floorspace F_k, gross value added (GVA) G_k, and business property value H_k at destination k, as well as the distance decay function with parameter γ based on travel cost (c_{jk}) between zone j and k.

$$E_{jk}^{l,m}(\tau + 1) = B_j^l P_j(\tau) F_k^{l,\delta_1} G_k^{l,\delta_2} H_k^{l,\delta_3} \exp(-\gamma^{l,m} c_{jk}^m) \tag{6}$$

$$= P_j(\tau) \frac{F_k^{l,\delta_1} G_k^{l,\delta_2} H_k^{l,\delta_3} \exp(-\gamma^{l,m} c_{jk}^m)}{\sum_z F_z^{l,\delta_1} G_z^{l,\delta_2} H_z^{l,\delta_3} \exp(-\gamma^{l,m} c_{jk}^m)} \tag{7}$$

Given that, we can sum the $E_k(\tau + 1)$ to obtain the updated employment demand at iteration $\tau + 1$, and then substitute the exogenous variable E_k in Eq. (1) with $E_k(\tau + 1)$. The recursive updating of employment and population continues until the model reaches numerical convergence, determined through changes in goodness-of-fit measures across iterations. Details of the convergence criteria, the model-split mechanism, baseline model calibration, and overall model performance are provided in Appendix A.

$$\begin{cases} E_k^l(\tau + 1) = \sum_k E_{jk}^l(\tau + 1) \\ P_j(\tau + 1) = \sum_j^l T_{ij}(\tau + 1) \end{cases} \tag{8}$$

4.4. Agglomeration effects and wider economic impacts

Using the modelled changes in the distribution of population and employment, we further examine the resulting agglomeration effects and changes in productivity. To quantify these effects, we apply an agglomeration index known as the Mean Effective Density (MED), which captures the influence of spatial proximity and economic scale. This index provides a quantitative measure of accessibility and the concentration of economic activities within a region (Graham and Gibbons, 2019).

Formally, the agglomeration index ρ_i at location i is defined as a distance-weighted sum of the surrounding economic mass m_j (e.g., employment or GVA), where the influence of distance is represented by a decay function $f(d_{ij})$ that captures the diminishing effect of spatial separation, as shown in Eq. (11):

$$\rho_i = \frac{1}{n} \sum_{j=1}^{n} m_j f(d_{ij}) \tag{9}$$

There are various choices for defining distance in agglomeration studies. Earlier works often relied on geometric distances, whereas more recent approaches adopt network-based travel times or generalised travel costs to better reflect actual travel conditions. In this study, we use average travel times weighted by multimodal flows (car and transit) to model the decay of agglomeration effects. We use the industry-specific distance-decay parameters reported by Graham et al. (2009) as reference values. Since their industry classification does not match ours exactly, we adopt the closest mapping: 1.746 for office and service, 1.818 for retail, and 1.562 for industrial. Other alternative distance-decay forms such as the negative exponential have also been tested.

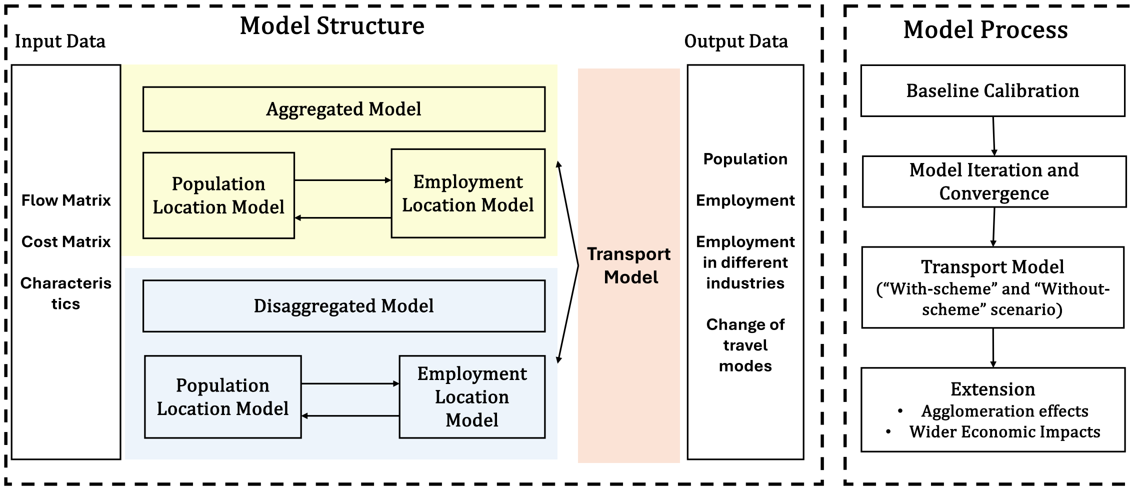
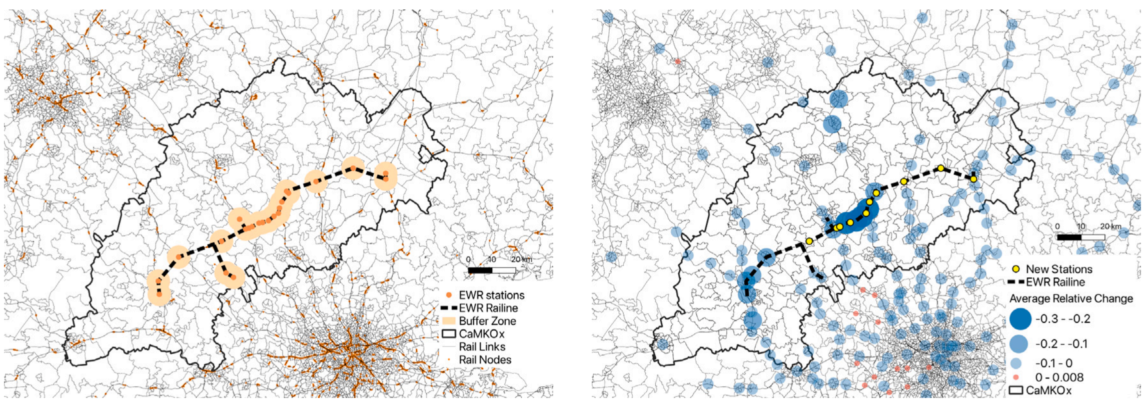


Fig. 5. General model structure and process.



(a) EWR Scenario Settings

(b) Average change in the proportion of travel time savings at rail stations

Fig. 6. EWR intervention and resulting travel time savings.

We further assess the wider economic impacts by linking changes in MED to productivity, measured through Gross Value Added (GVA). These impacts are quantified for four industrial sectors using the formulation from Department for Transport (2023b):

$$W_i^l = \left(\left(\frac{\rho_{i,A}^l}{\rho_{i,B}^l}\right)^{\theta^l} - 1\right) \cdot \left(\mathrm{GVA}^l \cdot E_i^l\right) \tag{10}$$

where W_i^l represents the productivity impact for industry l in zone i. $\rho_{i,A}^l$ and $\rho_{i,B}^l$ denote the agglomeration levels under scenario A and the baseline scenario B, respectively, and θ^l is the agglomeration elasticity for industry l. In this study, elasticity values of 0.024 for retail, 0.083 for the office and service sectors, and 0.034 for the industrial sector, are adopted from Graham et al. (2009). However, agglomeration elasticities vary across studies due to differences in study context, level of aggregation (firm-level or aggregate), data structure, and industry coverage. Some meta-analyses document substantial dispersion in reported elasticities and typically find higher elasticities for service activities than for manufacturing (Melo et al., 2009; Donovan et al., 2024). We therefore treat the elasticity values as a key modelling assumption and conduct a sensitivity analysis by varying each sectoral elasticity within ±50% of its baseline value, in 10% increments with the results reported in Appendix B.1.

GVA^l denotes the gross value added per worker, and E_i^l is the number of employees in industry l and zone i. The total wider economic benefit W is obtained by summing across all industries and zones:

$$W = \sum_i \sum_l W_i^l \tag{11}$$

Both aggregate and multi-sector versions of the recursive LUTI model are applied to simulate the impacts of the EWR project across England and Wales. The analysis focuses on the redistribution of population and employment across industries and travel modes. The baseline model is first calibrated and iterated until convergence, providing a stable reference scenario. Subsequently, an EWR intervention scenario, derived from the MOIRA transport model, is introduced to represent the rail accessibility improvements generated by the project (Department for Transport, 2024). Finally, the model assesses changes in economic concentration using the agglomeration index and extends the analysis to the national scale to capture interactions between the CaMKOx corridor and surrounding regions (see Fig. 5).

5. Results and discussion

5.1. EWR scenario — aggregate and disaggregate

5.1.1. Scenario settings

Following the calibration of the baseline model, the EWR scenario is implemented for cross-sectional analysis. Using the proposed alignments for railway infrastructure and station locations (East West

Railway, 2023), a 5 km buffer is generated around each station. This buffer distance reflects the maximum potential influence radius observed in comparable transport accessibility studies (Thornton et al., 2012; Jaber et al., 2022) (Fig. 6(a)). These buffers delineate MSOA zones likely to experience significant improvements in transit accessibility between origin–destination pairs. Based on this, the scenario incorporates adjustments to the updated GJT matrix to reflect post-EWR network conditions. The change ratios derived from the GJT updates are then applied to the travel time matrix used in the model. These GJT estimates are derived from the MOIRA model, a rail scheduling tool that estimates GJT and assesses how timetable changes affect passenger demand and revenue (Department for Transport, 2023c; Worsley, 2012). Within MOIRA, the behavioural "rooftop" assignment model is used, which estimates a passenger's likely choice of train by matching their preferred departure time to available services, minimising GJT across direct and connecting options. It accounts for passengers' preferred departure times and uses a weighted average of perceived journey times, based on logical train route choices, to estimate overall service attractiveness (Department for Transport, 2024).

The average change rates in GJT at each station are presented in Fig. 6(b). The results show that stations located in the central segment of the EWR corridor, particularly Milton Keynes, experience the most substantial reductions in GJT, with average improvements approaching 30%. Stations in the Oxford area also demonstrate considerable decreases, averaging around 15%. Several new stations along the EWR do not display a change because there is no pre-intervention station for comparison. In Greater London, there are slight reductions in travel time at some stations, while a small number of stations exhibit minor increases. These increases are primarily attributed to more frequent stops and longer waiting times, which marginally extend overall journey durations. This effect is observed at stations situated between London and the CaMKOx region, such as Amersham and Hemel Hempstead, as well as in parts of the northwestern corridor, such as Wolverhampton. The magnitude of these changes is negligible, with increases not exceeding 0.08 percent of total journey time.

5.1.2. Flows within the camkox corridor

Zooming in on the impacts of EWR within the CaMKOx corridor, the scenario results reveal notable shifts in the spatial distribution of population and employment, accompanied by changes in commuting behaviour across different transport modes. The improved transit accessibility within the CaMKOx corridor is expected to shift about 6% of baseline car users from car driving to public transit. Spatial patterns under the EWR scenario are characterised by a concentration of both population and employment around key nodes along the central segment of the railway, particularly in areas such as Milton Keynes and Bedford (Fig. 7). These locations benefit from substantial reductions in travel times due to the higher density of planned stations, which enhances their attractiveness for both residential settlement and employment relocation. Adjacent cities including Bicester, Oxford, and Cambridge also shows significant inflows of population and jobs, further strengthening their positions as urban centres within the regional network. Alongside the gains within the EWR corridor, the southern part of the region near London also experiences growth in population and employment. However, areas at the ends of the CaMKOx corridor, such as Swindon and Northampton, along with other peripheral zones, exhibit relative declines in their shares of population and employment. These patterns suggest a shift in economic and residential activities towards locations with improved transit accessibility.

To further examine the employment impacts, the disaggregated model presents changes across different industry sectors (Fig. 8). Overall, a similar spatial pattern is observed, with several MSOA zones in Oxford, Milton Keynes, and Cambridge experiencing the most significant increases. Among the sectors, the service sector, which accounts for the majority of employment in the CaMKOx region, experiences the largest shifts. Industrial employment shows modest growth, with relatively stronger increases in the northern part of the study area compared with other sectors. Changes in the retail and office sectors are smaller in scale and are concentrated in compact MSOA zones, typically within city centres where higher residential densities generate stronger local demand.

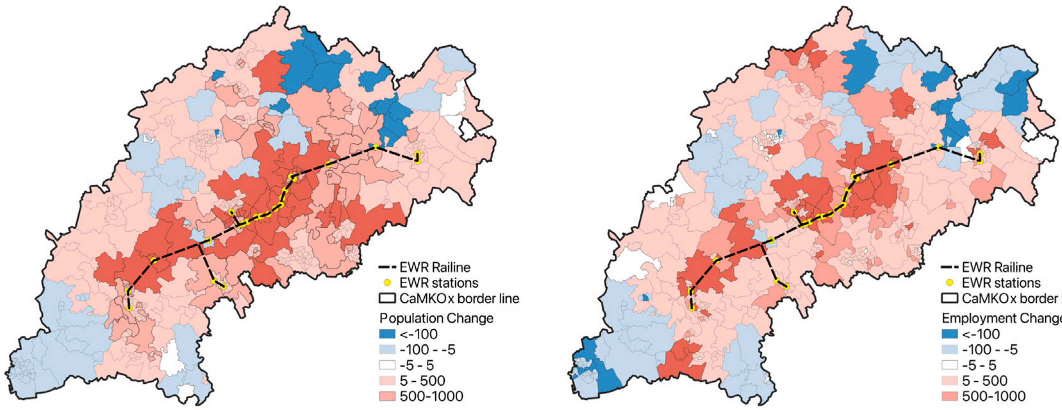
Generally, the EWR scenario promotes a more compact and transit-oriented spatial structure, intensifying development along the railway. These shifts in the distribution of population and employment are likely to have implications for future planning and land use policies in the corridor, which will need to take the emerging pattern of development into account.

5.1.3. Flows outside the CaMKOx corridor

Beyond the intra-corridor impacts of the EWR, we further examine its national-scale effects to assess how the project influences inflows into the CaMKOx region from external areas and where potential spatial displacement occurs. Generally, the EWR project may attract approximately 173,746 residents and 169,046 jobs into the CaMKOx area. Given the total population of around 3.3 million in the corridor, this corresponds to roughly 5 percent of the total. This relatively modest inflow partly reflects the fact that EWR improves not only connections to the CaMKOx corridor but also rail connectivity within other regions. As a result, people tend to relocate to areas closer to their original location that benefit from improved accessibility. For example, residents in London are more likely to move within London, such as to zones around Liverpool Street station with better rail connections to the CaMKOx corridor, rather than moving there directly. Fig. 9 indicates that zones surrounding the CaMKOx region, particularly those in the northern areas and around London, are likely to contribute inflows of residents and workers into the corridor. Methodologically, these relocation patterns result from the recursive LUTI model mechanisms. Commuting cost, income, housing prices and floorspace are treated as exogenous variables that serve as the fundamental economic drivers of relocation patterns. The high housing costs in London function as centrifugal forces. Conversely, the improvement in accessibility provided by the EWR reduces commuting costs, which in turn amplifies the relative attractiveness of the corridor's employment opportunities. In the northern areas outside the corridor, the model captures more significant displacement effects because these areas possess lower accessibility and less attraction compared with the core corridor nodes. The EWR intervention effectively recalibrates the trade-off between transport friction and these exogenous economic gradients. As the effective distance to the high-productivity centres of Oxford and Cambridge decreases, the model's spatial interaction mechanism shifts population and employment from these less competitive peripheral zones into the corridor's strengthened economic arc. The top ten areas losing population to the CaMKOx region are all located in London, particularly in west London. For employment, the largest outflows also originate from London, particularly from key employment centres such as the City of London and Westminster (Fig. 10).

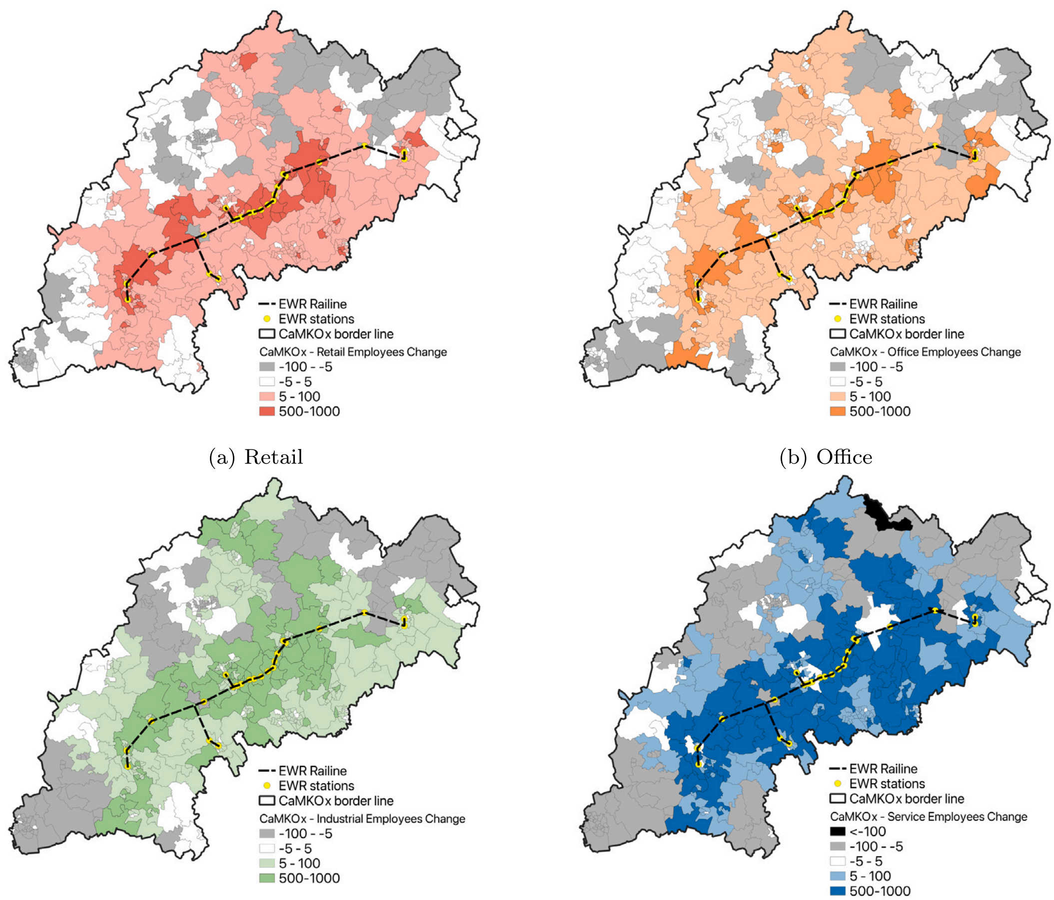
In addition, displacement effects are observed in northern cities adjacent to the corridor, such as Birmingham. Areas located farther from the region, including parts of Wales and northern England, also experience population and employment declines, reflecting adjustments to pre-existing travel patterns. Conversely, employment growth is evident in major cities further afield, such as Manchester and Leeds, while modest population increases emerge in several rural areas in the north. These spatial dynamics are largely driven by the enhanced connectivity of the national rail network, as EWR strengthens east–west linkages across regions.

Regarding the national impacts of employment by sectors, it shows distinctive patterns among the four sectors (Fig. 11). For the retail sector, displacement is most pronounced in areas adjacent to the northern part of the CaMKOx region, as well as in major northern cities such as Birmingham and Nottingham. The highest levels of displacement are observed in the north-eastern area around Peterborough. For the office



(a) Population redistribution after EWR (b) Employment redistribution after EWR

Fig. 7. Population and employment changes after EWR.



(a) Retail (b) Office

(c) Industrial (d) Services

Fig. 8. Employment change across different industries after EWR.

sector, the spatial pattern of employment relocation is more dispersed, with most movements originating from major surrounding cities. London, particularly the City of London, Westminster and Camden, shows the highest levels of relocation into the CaMKOx region. This pattern is largely related to the sectoral composition of the economy, as these areas comprise a large concentration of office-based employment. The industrial sector displays a comparable diffuse displacement pattern, with employment losses most pronounced in and around Peterborough.

Lastly, the service sector exhibits the strongest displacement effects, attracting employment from areas surrounding the CaMKOx region on all sides, as well as from more distant locations. London experiences the greatest losses in this sector, reflecting its dominant role in service-based industries. Since the service category includes education and other public and community services, this pattern is also consistent with the corridor's higher-education and research presence centred on Oxford and Cambridge. Meanwhile, the areas connecting London and

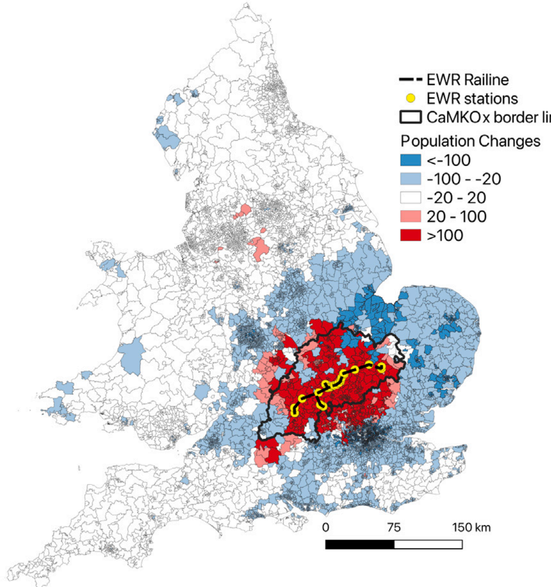


Fig. 9. National Population after EWR.

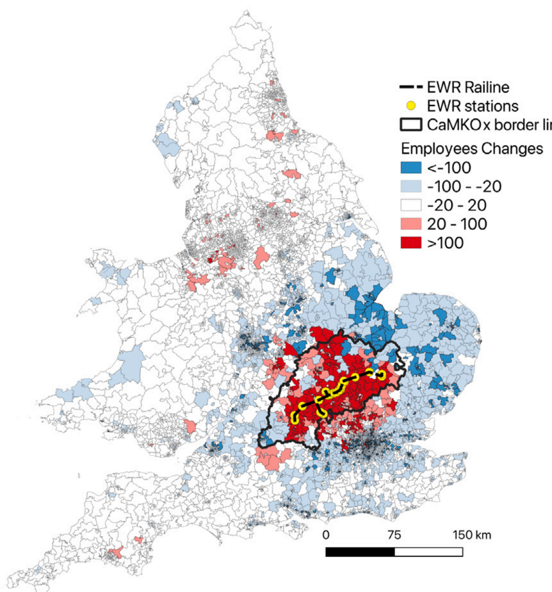


Fig. 10. National Employment after EWR.

(a) Retail

(b) Office

(c) Industrial

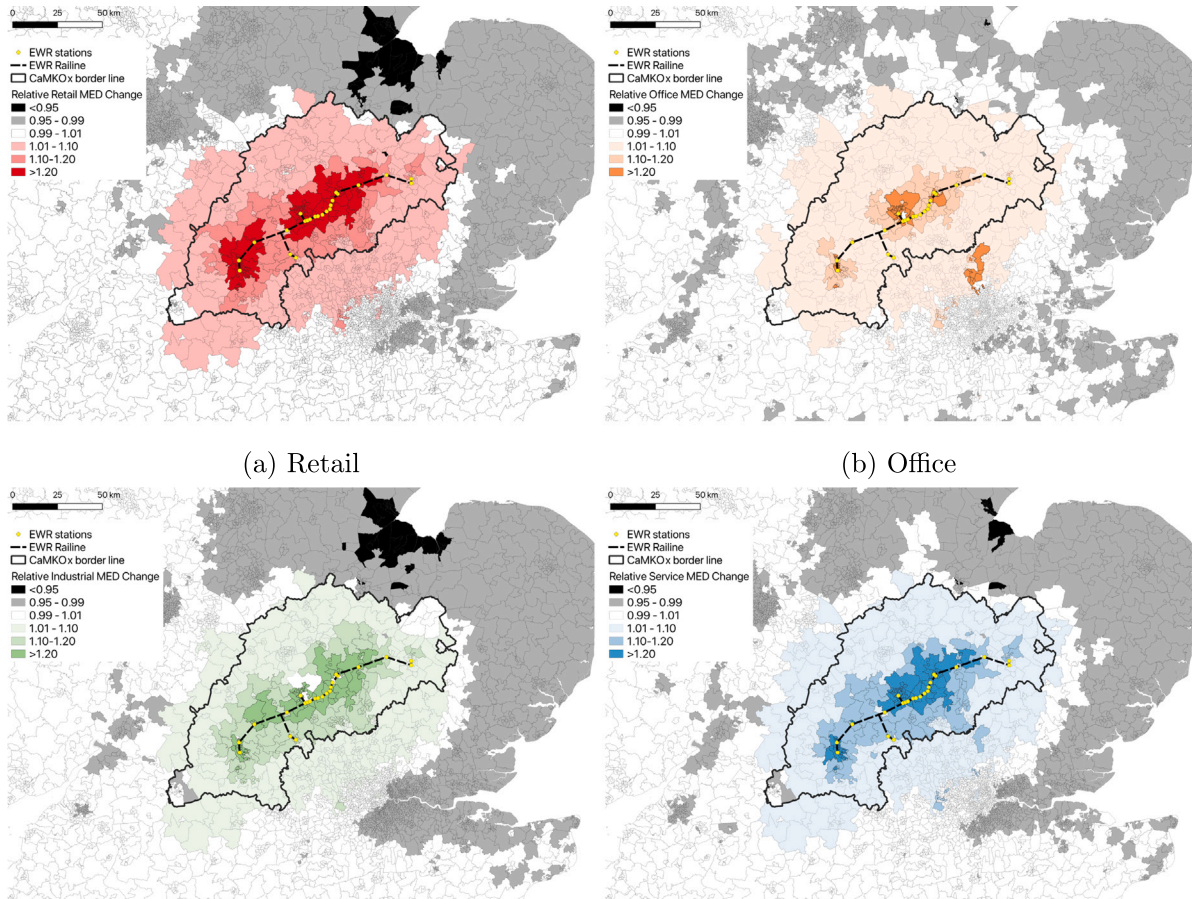
(d) Service

Fig. 11. Employment changes by sector.

the CaMKOx corridor show notable employment growth, likely driven by high housing and business costs in London that encourage firms to relocate to more affordable locations with improved connectivity and less relocation costs.

5.1.4. Scenario results — agglomeration effects and wider economic impacts

Building on the observed displacement of employment and population across different industries, we further explore whether these spatial redistributions can lead to agglomeration effects and productivity changes. This leads to the question of whether the EWR project contributes to net economic growth, or merely reallocates existing economic activity across space. Fig. 12 shows the agglomeration effects changes for four sectors. In the EWR scenario, agglomeration within the CaMKOx corridor increases, as jobs flow in from less connected areas and concentrate more strongly around key nodes such as Bedford, Oxford and Milton Keynes. Moderate spillover effects are also observed in peripheral zones outside the corridor. However, a decline in agglomeration is evident in the eastern part of England, particularly across rural areas. The retail and office sectors show the largest increases in MED, concentrated around major urban centres such as Oxford, Milton



(a) Retail (b) Office

(c) Industrial (d) Service

Fig. 12. Sector-specific changes in mean effective density (MED), reported as change indices relative to the baseline scenario, where 1 indicates no change.

Keynes and Bedford, where accessibility improvements are greatest. These areas form the core of the emerging high-density economic cluster within the corridor. In contrast, the industrial sector shows a more dispersed pattern of moderate MED increases extending along the corridor and into adjacent towns (Glaeser and Kahn, 2001). This may reflect characteristics of industrial activities, which typically require larger sites and are less dependent on high-access locations than the service sector. The service sector displays the widest area of MED gains, extending beyond the CaMKOx area into neighbouring regions.

Overall, the observed spatial heterogeneity across sectors indicates that the EWR investment reinforces existing agglomeration centres while also diffusing accessibility benefits into surrounding regions. This sector-specific variation suggests that the productivity impacts of the EWR are likely to be uneven, with stronger effects in knowledge and consumer oriented sectors and more moderate outcomes in production based industries.

Building on the sectoral analysis of mean effective density, the next step is to assess whether such spatial concentration translates into productivity gains at both regional and national levels. Fig. 13 presents the estimated productivity impacts of the EWR project. The gains are clearly concentrated within the CaMKOx corridor, with the largest improvements around Oxford, Milton Keynes and Bedford, where accessibility increases are greatest. Positive effects are also observed in parts of central and west London. This reflects the fact that the model captures changes across the wider rail network rather than only along the EWR corridor, so altered accessibility in some parts of London can also contribute to productivity gains there. The largest estimated productivity gains are observed in these areas like Milton Keynes, with some zones exceeding £1 million. This reflects stronger agglomeration within the corridor and improved east–west connections between the main centres. As shown in Table 2, under the standard scenario the total GVA uplift is estimated at £589.09 million within the CaMKOx region, compared with £347.57 million at the national level.

Within the CaMKOx corridor, the estimated GVA uplift is equivalent to about a 0.7% increase relative to the corridor's existing GVA. At the national level, the corresponding uplift represents only around a 0.02% increase relative to total GVA in England and Wales, which indicates a more modest net effect that reflects displacement. Relative to the current EWR base cost estimate of £4120 million reported by East West Railway Company (2024), the estimated national uplift is equivalent to about 8.4% of the investment cost. Sensitivity tests based on a ±50% variation in the agglomeration elasticity suggest that the national-level estimate ranges from £172.46 million to £525.34 million, while the corresponding estimate for the CaMKOx corridor ranges from £299.63 million to £749.08 million.

Because the analysis aims to reflect post-pandemic economic conditions, we also consider the implications of hybrid working. Using 2024 industry-specific shares of hybrid workers reported by the ONS (Office for National Statistics, 2024), we introduce sector-specific adjustment factors to moderate the commuting-related effects of improved rail accessibility. This hybrid working scenario captures the reduced intensity of workplace commuting and the weaker spatial concentration and relocation effects expected in sectors with higher hybrid working prevalence. The detailed adjustment procedure is described in Appendix B.2. Under this hybrid working scenario, the corridor-level GVA uplift falls to £359.56 million, while the national total rises modestly to

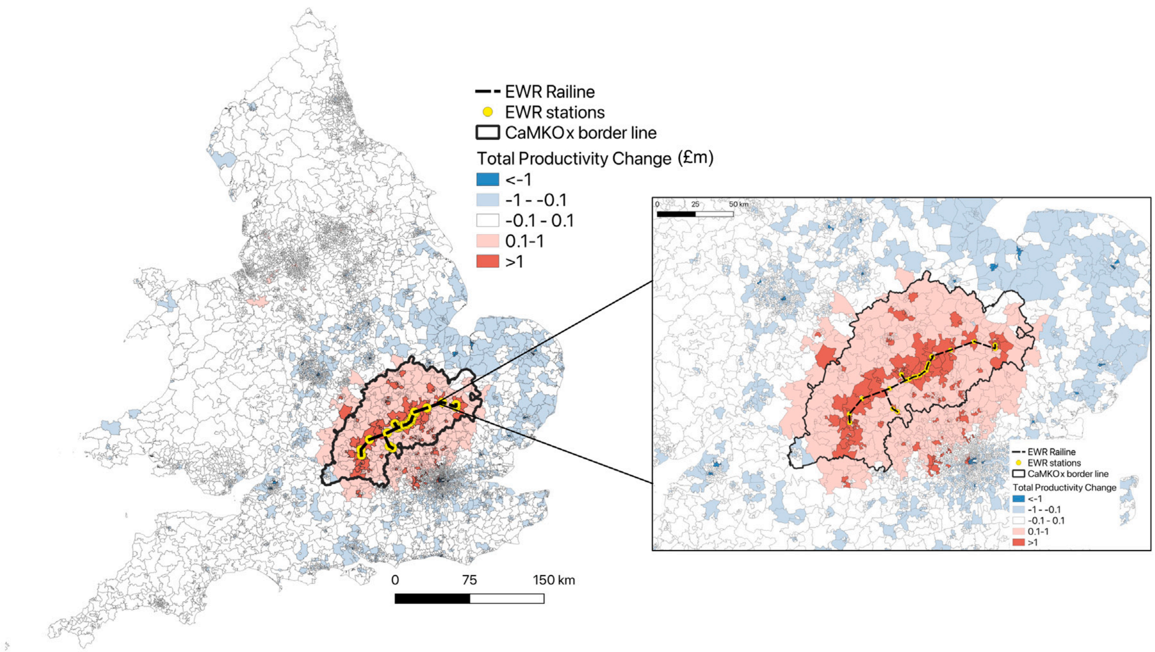


Fig. 13. Productivity Impacts from the EWR Project (£million)

Table 2
Estimated GVA impacts of EWR under the standard, hybrid working scenarios by sector and geography with uncertainty bands.

Sector	Main scenario (Standard)	Hybrid work (Post-pandemic)	Uncertainty band (Lower–Upper)
National level(£million)	**347.57**	**370.39**	[172.46–525.34]
Retail	38.65	36.31	[19.28–58.10]
Office	66.25	86.77	[32.65–100.82]
Services	211.54	217.48	[105.02–319.58]
Industrial	31.13	29.82	[15.51–46.81]
CaMKOx region(£million)	**589.09**	**359.56**	[299.63–749.08]
Retail	48.03	43.38	[23.98–72.16]
Office	178.71	124.22	[89.01–269.12]
Services	298.69	289.30	[148.70–450.00]
Industrial	63.66	58.59	[31.78–95.64]

Notes: The reported values represent model-estimated differences in GVA between scenarios. They are not expressed as discounted present values, as no explicit assumptions are made about the price base, discounting, or the timing of impacts. They should therefore be interpreted as indicative comparative estimates rather than formal appraisal totals. In the text, these estimates are benchmarked against 2024 GVA levels for the CaMKOx corridor and for England and Wales. Uncertainty bands reflect a sensitivity test of ±50% around the agglomeration elasticity.

£370.39 million. This pattern suggests that hybrid working weakens the concentration of gains within the corridor and reduces displacement effects elsewhere, particularly in office-based activities. As a result, the national net effect rises slightly despite the smaller local uplift in CaMKOx. One reason may be that fewer office workers in highly agglomerated areas such as the City of London choose to relocate to the CaMKOx corridor under hybrid working. This would reduce the losses outside CaMKOx relative to the standard scenario. Sectorally, services account for the largest share of GVA gains in both scenarios, followed by office activities, while retail and industrial sectors make smaller contributions.

Overall, the observed spatial heterogeneity across sectors shows that the EWR investment reinforces existing agglomeration centres while extending accessibility benefits to nearby regions. Productivity effects are uneven, with stronger gains in knowledge intensive and consumer oriented sectors and smaller improvements in production-based industries. While these changes enhance spatial efficiency and connectivity within the CaMKOx corridor, their contribution to national productivity appears limited, as part of the gains reflect a redistribution of existing activity. Realising the full potential of the EWR will therefore depend on complementary place-based strategies that promote collaboration, innovation, and local capacity to convert accessibility improvements into sustained economic growth.

6. Conclusion

This study develops a new recursive land use and transport interaction (LUTI) model to simulate the large-scale impacts of infrastructure investment, using the East-West Rail (EWR) project as a case study. By integrating a calibrated gravity model with dynamic redistribution mechanisms, the model investigates how improved regional connectivity alters the spatial distribution of population and employment at a national scale. Furthermore, the study demonstrates how LUTI models can be extended to support large-scale transport investment by capturing wider economic impacts, such as agglomeration effects.

Several limitations of this study should be acknowledged. First, the model assumes that accessibility improvements translate immediately into redistribution effects, without accounting for temporal lags in migration, real estate development and labour market adjustments. Second, it does not incorporate feedback mechanisms, such as changes in housing prices or employment densities, which could influence relocation choices in a non-linear manner. Third, in the disaggregated model, the sectoral analysis is based on a four-sector classification due to data limitations. This means we cannot separate competition inside each sector, so we report results only at the aggregated four-sector level. Some specific dominant industries may be neglected like innovation and education within the corridor, which can be improved in the future with more detailed and context-led sector disaggregation. Fourth, given the difficulty of modelling realistic travel times at a large spatial scale, several necessary simplifications were made. For example, the model does not account for congestion effects, assumes that travel behaviour is determined solely by journey time (excluding other potential factors such as monetary cost), and does not incorporate possible variations in floorspace supply. In addition, active modes are not considered in the model, which may affect the results, especially for internal trips. This may lead to an underestimation of displacement effects, as well as mean effective density (MED) and productivity changes within zones.

These limitations highlight opportunities for future improvement, such as incorporating more comprehensive variables like generalised travel cost, and integrating economic mechanisms related to the land market. However, adding these would also increase the complexity of the model and limit its applicability and transferability. At the current stage, the model achieves reasonable accuracy and stability, performs well for large-scale analysis, and maintains sufficient spatial granularity, all while requiring only modest computational effort and accessible run times.

Lastly, the estimation of productivity gains was conducted without incorporating general equilibrium effects and also neglects population growth and international migration, which may lead to different outcomes. Future studies could address this by applying structural economic modelling if more detailed or system-wide outputs are required. Nevertheless, the simplified framework adopted here enables a clearer and more transparent interpretation of the direct relationship between accessibility improvements and productivity outcomes.

This study provides a practical demonstration of how transport-induced agglomeration and displacement effects can feasibly be estimated at a high spatial resolution. By applying the recursive model at the national scale, we are able to trace how changes in accessibility reallocate employment and population beyond the corridor and to examine displacement effects. Despite this national coverage and disaggregation by industry and transport mode, the model retains a relatively simple structure and can be run quickly for policy scenarios. In practice, the appropriate balance between model complexity and practical feasibility should be determined according to the requirements and context of each project, which remains an important area for future exploration.

CRediT authorship contribution statement

Zhixuan Liu: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Jens Kandt:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Fulvio D. Lopane:** Writing – review & editing, Supervision, Methodology. **Robin Morphet:** Writing – review & editing, Methodology. **Michael Batty:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2026.104681.

Data availability

Data will be made available on request.

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