Transport Appraisal and Economic Density – Scoping Study

Final Report

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Executive Summary

This technical report sets out the scope for a large-scale re-estimation of the agglomeration parameters applied in the Department for Transport (DfT) Transport Analysis Guidance (TAG), wherein agglomeration impacts for transport schemes are appraised within Cost Benefit Analysis (CBA).

The report reviews developments in the literature on agglomeration and transport appraisal, specifically, in relation to some key themes identified by the DfT as areas of improvement for the wider economic impacts (WEI) assessment framework. The underlying aim is to assess whether and how they can be incorporated in the scope for a future re-estimation study. A condensed list of the themes is provided below.

a) Eliminating overlap between the WEIs of agglomeration and the other categories of impacts assessed in the TAG methodology.

b) Distinguishing the two main types of agglomeration economies in appraisal calculations: urbanisation economies and localisation economies.

c) Appraising amenity and consumption externalities and wider relocation costs within TAG.

d) Disentangling contributions from the micro-mechanisms of agglomeration, namely: sharing, matching and learning

e) Identifying appropriate access to economic mass (ATEM) measures of agglomeration for modelling ‘real’ versus ‘effective’ density benefits.

f) Understanding the spatial scope of agglomeration economies in terms of distance-decay and addressing concerns related to the modifiable arial unit problem.

g) Accounting for non-linearities and endogeneity biases in empirical estimation.

h) Quantifying heterogeneity in agglomeration parameters, for instance, by area type and mode of travel.

Following the review, the report provides recommendations for theoretical and empirical work to be conducted as part of the future re-estimation exercise.

The analysis in this report is directed towards two distinct evaluation criteria. First, is it possible to perform unbiased (preferably causal) estimation of the key parameters of interest in WEI appraisal using the available data and state-of-the-art econometric methodology? Second, are the estimated parameters suitable for direct application in the economic model underpinning TAG? If not, is it possible to apply minor methodological adjustments in the overall TAG approach to ensure theoretical coherence?

Before turning to theme-specific conclusions, we would like to make a general point. The report identifies a mismatch between the Department’s ambition to achieve significant methodological improvement in the estimation of WEIs on the one hand, and the pace of progress in the academic literature on the other hand.

The academic literature on transport appraisal has been relatively static in recent years. More significant developments have been made in the urban/spatial economics community, but most of their findings have not been translated into practice-ready solutions for appraisal; and in many cases this task does not seem trivial. Assimilation of this literature in appraisal cannot be part of the scope of a short-term re-estimation of TAG parameters, but it does provide considerable scope for more fundamental research. We recommend that the Department explore the means through which innovation in this heavily policy-relevant field of research can be supported and, if necessary, incentivised.

Table 1: Classification of WEI improvement areas by empirical evidence in the literature

Agenda items	Conceptual ideas with no empirical evidence	Empirical evidence on the existence of the mechanism	Identification and separation from other channels of agglomeration	Identification of a parameter/elasticity which fits the current TAG framework
Overlap of direct and wider impacts			☑	
Distinction between urbanisation and localisation	☑			
Consumption and amenity externalities		☑		
Wider relocation costs		☑		
Contributions from different ‘micro-mechanisms’		☑		
‘Real’ and ‘effective’ density benefits				☑
Impedance measures				☑
Functional form of decay parameters				☑
The level of spatial aggregation				☑
Endogeneity issues and validation methods				☑
Non-linearities in functional forms				☑
Heterogeneity in parameters				☑
Differential elasticities by mode				☑
The role of active travel				☑

The report concludes that the proposed improvement areas are underpinned by existing empirical evidence to varying degrees. Table 1 assigns the themes to four categories. For the first five areas, empirical evidence is either (i) non-existent, or (ii) only proves the *existence* of an underlying mechanism without precise estimates of magnitudes, or (iii) even if magnitudes can be estimated, they include multiple channels of agglomeration impacts not separable from each other. The remaining themes in Table 1 can be underpinned by empirical evidence in such a way that the estimates may be directly applicable in TAG.

After the detailed analysis of the proposed areas of methodological and empirical expansion, the report concludes with the following recommendations for future work.

R1 Double-counting concerns should be addressed by redesigning the fundamental approach to calculate WEIs of agglomeration. For this purpose, a zone-level productivity model where the productivity effects arising from both cost savings and agglomeration externalities are estimated together is recommended for investigation.

R2 There is a need for theoretical/ conceptual work on the distinction between urbanisation and localisation effects as a necessary precursor to developing empirical solutions for appraisal. Accordingly, models that differentiate between these effects should be estimated to assess whether the resulting evidence is appropriate for utilisation in appraisal.

R3 Incorporating consumption and amenity externalities in partial equilibrium transport appraisal is a challenging task on the research agenda. Future research should define the empirical estimands (for instance, a price index elasticity or location attractiveness elasticity) that such a partial equilibrium approach requires, and develop a narrative, and the associated theory, that address the double counting concern in case of this type of externality.

R4 Contributions from distinct micro-mechanisms of agglomeration (sharing, matching, and learning) should be estimated via models that exploit natural experiments where enough variation in the contributions can be guaranteed with some of the micro-mechanisms kicking in and some not. Consideration should be given as to whether the resulting evidence is suitable for use in appraisal.

R5 Estimation of real density-driven benefits of agglomeration should be conducted by exploring novel measures of impedance for ATEM variables, including potential measures that combine observed travel flows (trips) and generalised travel costs (GTCs).

R6 Estimation of the spatial scope (decay) of agglomeration economies should be done by implementing and comparing alternative approaches to model decay, including modelling the decay function flexibly via semi-parametric regression. Judgement should be made to identify the form that is both analytically tractable and best approximates the observed pattern of decay.

R7 Sensitivity of agglomeration elasticities to zonal definitions should be tested by estimating the agglomeration model with data aggregated at different spatial levels. Results should be compared to identify which evidence is more robust and suitable for utilisation in appraisal.

R8 Adjustments for observed and unobserved confounding and reverse causality should be made within the econometric model of agglomeration to obtain agglomeration elasticities that are robust and suitable for use in appraisal.

R9 The econometric model of agglomeration should be designed to capture potential non-linearities of agglomeration effects, which can be achieved by flexibly modelling the agglomeration-productivity relationship using non-parametric or semi-parametric regression. Implications of the results for appraisal should be evaluated.

R10 Econometric models that can yield heterogeneous agglomeration effects by area type, by functional classification of firms, and by trip purpose should be estimated, for instance, by estimating separate agglomeration elasticities for relevant sub-samples of the data. The suitability of the resulting estimates for use in appraisal should be assessed.

R11 Due to econometric challenges arising from severe multicollinearity, estimating mode specific agglomeration elasticities is not recommended.

Table 2 provides a summary of our recommendations by classifying the areas of improvement by feasibility. We find that three themes, (i) the concerns about endogeneity and validation, (ii) non-linearities in the functional dependence between productivity and agglomeration, and (iii) heterogeneity in agglomeration elasticities, can by successfully implemented via immediately available methods. In the remaining areas of methodological improvement, the report finds that further fundamental research is unavoidable. In some cases, either the limitations of the economic model of TAG or econometric challenges make a future implementation unlikely, based on our understanding of the existing literature.

Table 2: Classification by the ease of implementation in a future TAG update

Agenda items	Method is available, ready for estimation/re-estimation	Implementation seems feasible in TAG, but further theoretical and/or empirical research is needed	Implementation is unlikely in current TAG, but potentially feasible in general equilibrium	Implementation is unlikely due to econometric challenges (e.g. equivalence of outcomes)
Overlap of direct and wider impacts		☑		
Distinction between urbanisation and localisation				☑
Consumption and amenity externalities			☑	
Wider relocation costs			☑	
Contributions from different 'micro-mechanisms'				☑
'Real' and 'effective' density benefits		☑		
Impedance measures		☑		
Functional form of decay parameters		☑		
The level of spatial aggregation		☑		
Endogeneity issues and validation methods	☑			
Non-linearities in functional forms	☑			
Heterogeneity in parameters	☑			
Differential elasticities by mode		☑		
The role of active travel		☑		

At this point, it is worth emphasising that each step in the calculation of the welfare impacts of transport investments involves several inherent uncertainties, for instance, those resulting from the data and the model itself, which is just an abstraction of the associated real-world phenomenon. Moving ahead, it remains crucial that the Department adopts a stochastic outlook towards CBA to have a clearer account of these uncertainties. This can be done, say, by considering the standard errors in the predicted benefits.

The report makes another important contribution by delivering an alternative economic model of transport appraisal that is able to capture a wider set of general equilibrium welfare effects than the partial equilibrium approach of TAG. We demonstrate that this benchmark model is suitable to test double counting concerns in TAG. The report documents an illustrative application of a baseline benchmark model in which a hypothetical transport improvement is simulated in a synthetic environment. Our initial experiment suggests that the sum of direct user benefits and Level 2 agglomeration impacts, calculated according to TAG, is unlikely to generate double counting concerns.

1. Introduction

This document sets out the scope of a future empirical project aimed at a large-scale re-estimation of the agglomeration parameters applied in the Department for Transport (DfT) Transport Analysis Guidance (TAG).

The re-estimation of the agglomeration parameters applied in TAG is needed for the following reasons.

- The current parameters were estimated in the late 2000s. Better data sources, such as highly disaggregate data on origin-destination travel flows, have become available since then.
- There is an opportunity to rely on state-of-the-art econometric tools, especially when it comes to treating endogeneity concerns, which are widely recognised in the agglomeration literature. In relation to this objective, it will be beneficial to inscribe the entire empirical exercise within a causal inference framework.
- Several concerns have been expressed by practitioners with regards to some technical features of the studies underpinning the current TAG. These issues need to be addressed, also in light of technical improvements that have been proposed so far. Key concerns include: the structure and components of the Access To Economic Mass (ATEM) measure; potential differentiations of the agglomeration elasticity (for instance, sectoral, geographical and distance-dependent); the distinction between urbanisation and localisation economies; the type of outcome measure (whether total factor productivity or wages); the type of impedance measures (for instance, generalised costs, travel times and distance); and the nonlinearity of the agglomeration-productivity relationship.
- The recent spatial economics literature has generated evidence on the importance of consumption externalities as foundations of agglomeration. The re-estimation project should explore whether and how these additional benefits could be represented as WEIs in appraisal.

The report follows a list outlined by the DfT on the lines along which the estimation of agglomeration elasticities is expected to improve. A condensed list of these themes is provided below.

a) Eliminating overlap between the wider economic impacts (WEIs) of agglomeration and the other categories of impacts assessed in the TAG methodology.

b) Distinguishing the two main types of agglomeration economies in calculations: urbanisation economies and localisation economies.

c) Appraising amenity and consumption externalities and wider relocation costs within TAG.

d) Disentangling contributions from the micro-mechanisms of agglomeration: sharing, matching and learning

e) Identifying appropriate access to economic mass measures of agglomeration for modelling ‘real’ versus ‘effective’ density benefits.

f) Understanding the spatial scope of agglomeration economies in terms of distance-decay and addressing concerns related to the modifiable arial unit problem.

g) Accounting for non-linearities and endogeneity biases in empirical estimation.

h) Quantifying heterogeneity in agglomeration parameters, for instance, by area type and mode of travel.

Our report confirms that each item in this list is well founded and justified by recent developments in the urban and transport economics literatures. The ultimate aim of the scoping study is to provide recommendations about the depth and scope of the theoretical and empirical work to be conducted as part of the future re-estimation exercise, analysing each item in the list separately.

The central focus of the study is empirical in nature as its primary objective is to outline the scope of future empirical work. However, we pay particular attention to the fact that the estimated parameters (for instance, agglomeration elasticities) will be applied in a specific economic model: the appraisal model of TAG. This fact is important because the specification of the empirical models should remain coherent with the theoretical structure of the economic model in which the estimates are applied. It may well be the case that an empirical methodology in the agglomeration literature provides unbiased estimates of a measure of agglomeration impact, but the measure is not compatible with the structure of TAG. In this sense we investigate two requirements simultaneously in this scoping study: empirical robustness and theoretical coherence.

The scoping study assumes that the core appraisal framework of TAG wherein the welfare impacts of transport interventions (that is, TAG Level 2 & 3 impacts) are derived as additively separable elements to the direct user benefits (TAG Level 1 impacts) is to be maintained. In other words, while the empirical methodology behind the estimates should be improved in the re-estimation study, the way the newly estimated parameters enter the appraisal model will not change significantly. As an intermediate deliverable of this project, we submitted a report on a Conceptual Economic Framework (CEF) of transport appraisal. The CEF provides an overview of three channels through which the transport improvements should lead to additively separable welfare effects in TAG appraisal. The CEF explain why potential spillovers between the three channels may lead to overlap and/or confounding between Level 1, Level 2 and Level 3 welfare effects. Section 2 of the current report is a summary of our previous CEF report.

Sections and 3 and 4 cover the core assessment performed in this project from an empirical perspective. Section 3 details conceptual matters in three steps. First, we discuss how an empirical specification must be defined to ensure that the direct user benefits of the transport improvement are isolated from wider impacts through the agglomeration externality. The section considers multiple ways in which the econometric model of the estimation of agglomeration elasticity can be reformulated in light of this aim. Second, we review the theoretical justification for separating urbanisation and localisation economies in appraisal. We review potential quantitative challenges that emerge in the form of equivalent outcomes when urbanisation and localisation mechanisms take effect simultaneously. Third, in Section 3.3 we assess new empirical evidence on consumption and amenity externalities and conclude that their quantification in transport appraisal is not established yet in the literature.

Section 4 concentrates on more technical subjects related to data collection, the choice of outcome and explanatory variables and the specification of regression equations in agglomeration estimation. This section follows very closely the themes outlined by the DfT in the bid call. Each of the eight subsections conclude with a summary of the main lessons distilled from the literature and our recommendations for the re-estimation of agglomeration elasticities for TAG.

Section 5 of the report is devoted to a novel tool that we developed in support of future methodological work in the context of transport appraisal and wider economic impacts. The section introduces a spatial general equilibrium model that we use as a benchmarking tool to assess the critical parts of the partial equilibrium framework of TAG. General equilibrium models are not suitable to break down welfare effects the same way as TAG but their aggregate welfare measures are less prone to double counting as they handle multiple sectors (the transport, labour and housing markets, specifically) in an integrated fashion. This section includes a baseline prototype of such a benchmark model to illustrate how this approach can be applied to confirm the aggregate outcome of partial equilibrium appraisal.

In Section 6 the report presents further aspects of transport appraisal and economic density linked to the post-COVID world in which working from home (WFH) becomes more prevalent. Our review of the latest literature confirms that WFH makes the re-estimation of agglomeration elasticities more relevant than ever. We also highlight that the reduction in personal interactions between workers implies new ways in which agglomeration economies should be interpreted, but the fundamental motivation of densifying economic activity is unlikely to change.

The concluding Section 7 of the report revises the overall lessons of this project and reiterates our recommendations about the re-estimation of WEI parameters for transport appraisal in the UK.

2. Conceptual economic framework of transport appraisal

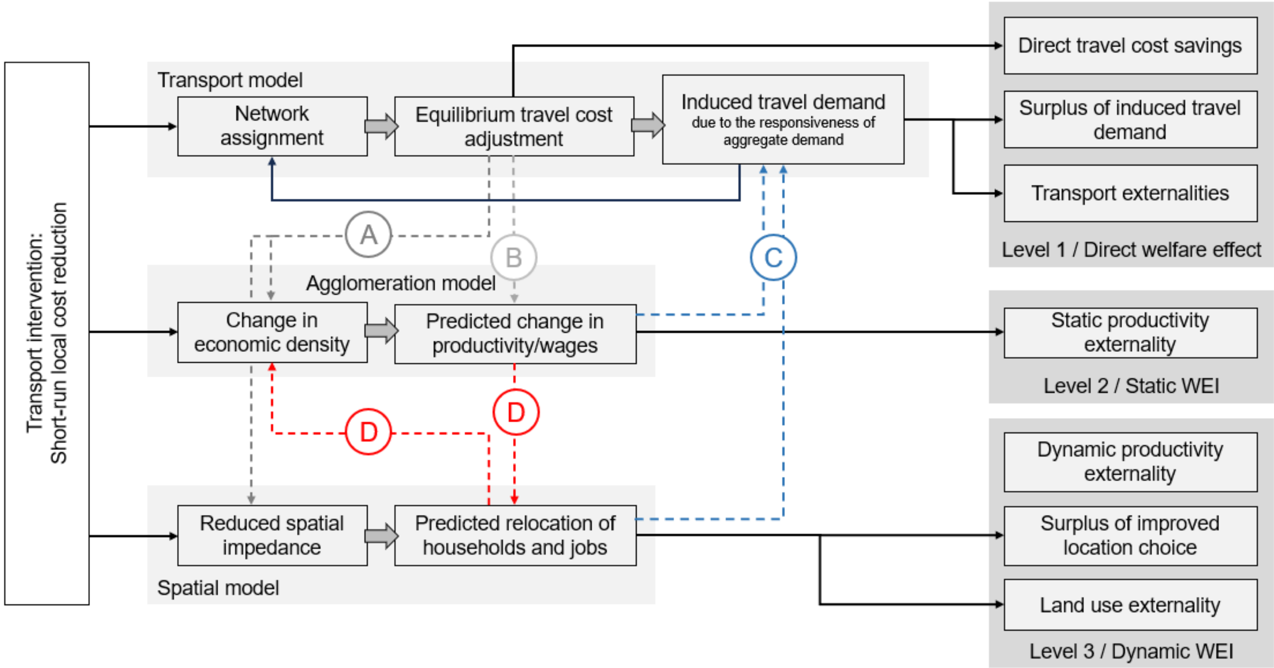
The project behind this scoping study started with a deeper conceptual phase in which our aim was to define the economic framework of transport appraisal, focusing on potential pitfalls that lead to bias in evaluation. The outcome of that phase has been documented in an intermediate deliverable titled ‘Conceptual Economic Framework’. This section provides a brief summary of the conceptual economic framework (CEF) underlying the appraisal of transport induced agglomeration impacts.

The appraisal practice of TAG derives the welfare impacts of transport interventions as *additive* elements that are the outcomes of three partly or fully separated models:

1) a transport model measuring the direct user benefits (DUBs) for both existing and new users generated via changes in the generalised travel costs (GTCs) and quality of service, and transport-related externalities (say, pollution and accidents) of the intervention,
2) an agglomeration model quantifying the wider agglomeration benefits, and
3) a spatial model measuring other externalities related to the relocation of firms and households.

Figure 1 illustrates the three models in an integrated framework, where the inputs and outputs of these models can be identified via the horizontal linkages indicated by solid black arrows.

Figure 1: Combination of the transport, agglomeration, and spatial models in an integrated framework



The core insight of the CEF, also drawn into this Figure, is that potential spillovers may exist between the three models that pose a serious threat of double counting of welfare impacts. These channels of spillovers, marked using vertical dashed arrows in the above figure, are briefly summarised below:

A. Agglomeration benefits are quantified by predicting changes in economic density (represented by ATEM) caused by the reduction/increase of impedance between locations through the transport network, and the relocation of firms and households. Impedance is directly affected by the transport policy on specific links. At the same time, traffic may rearrange in the entire transport network so, essentially, impedance may change on every single link of the network. The threat is that this change in impedance may be taken into account as a Level 1 direct user benefit (or disbenefit), a Level 2 WEI through the static change in economic density, and a Level 3 WEI through relocation benefits (or disbenefits). This spillover between Levels 1 and 2 is represented in the Figure by link A.

B. Firm output is affected through channels other than changes in density. For instance, firms use transport as a factor input to production and thus a reduction in the equilibrium transport cost implies higher output even without externalities of agglomeration. This may lead to double counting between direct travel cost savings and the WEIs of agglomeration.

C. Transport interventions may induce new travel demand via three channels: direct reduction in the GTCs, agglomeration benefits, and relocation of economic agents (firms, workers, and households). In principle, the economic impacts arising from the latter two channels are to be accounted for Level 2 and Level 3 WEIs, rather than being included in Level 1 calculations of the surplus of induced travel demand, as this may possibly lead to double-counting.

D. The final challenge of empirically distinguishing between static (Level 2) and dynamic (Level 3) WEIs of agglomeration, emphasising the need to discern whether productivity gains stem from enhanced individual firm performance or the displacement of less productive firms by more efficient ones through spatial relocation. This challenge emerges because the observed change in economic density may be a result of firm relocation (spatial sorting) instead of the incumbent firms becoming more productive.

This conceptual understanding of the chain of impact of transport policies and potential spillovers between the three levels of appraisal remains an important guiding principle in the rest of this report. We draw important conclusions for both the empirical work in Section 3 and 4 (for instance, avoiding overlap between direct and wider impacts in 3.1), and the benchmark general equilibrium model in Section 5. We recommend that future research on the methodology of WEI estimation should rely on similar conceptual grounds.

3. Estimating the wider economic impacts of agglomeration

3.1 Overlap of direct and wider impacts

R1	**Recommendation: Double-counting concerns should be addressed by redesigning the fundamental approach to calculate WEIs of agglomeration. For this purpose, a zone-level productivity model in which productivity effects arising from both cost savings and agglomeration externalities are estimated together is worthy of investigation.**

The evaluation of impacts in Cost-Benefit Analysis (CBA) adheres to the principle of additionality, which emphasises that distinct impacts considered in the assessment should not overlap. As mentioned in Section 1, this fundamental principle forms the basis of the DfT TAG method for appraisal. Consequently, while it is important for CBA to encompass as many impacts as feasible, comprehensiveness should not result in the duplication of counts.

This report concerns the wider economic impacts (WEIs) of transport schemes stemming from agglomeration economies. For a given distribution of economic entities such as workers, businesses, and consumers across geographical areas, improvements in transport connectivity lower the costs associated with interactions among these entities, thus boosting their effective density. Existing literature indicates that such boosts in effective spatial concentration yield advantages in production, which are supplementary to the direct user benefits (DUBs) arising from changes in generalised travel costs (GTCs)[1].

For these WEIs of agglomeration (TAG Level 2 impacts) to be considered supplementary, it is crucial that the agglomeration elasticity primarily captures an external scale effect, independent of other transport cost factors (such as time and monetary expenses) that potentially scale with economic density represented by access to economic mass (ATEM).

3.1.1 Overlap concerns

The potential double counting issue addressed here is that there might be redundancy in the productivity elasticity with respect to ATEM, as it could encompass productivity impacts already accounted for in other aspects of evaluation (TAG Level 1 and 3 impacts). The review of the existing CEF of TAG identified two key empirical concerns that are relevant to the estimation of WEIs of agglomeration:

a) Overlap between TAG Level 1 and TAG Level 2 impacts that arises due to the influence of time-dependent productivity impacts generated via reductions in GTCs (links A and B in Figure 1)

b) Distinguish TAG Level 2 (static) WEIs of agglomeration from TAG Level 3 (dynamic) WEIs that arises due to spatial sorting and relocation of firms and workers by productivity (link D in Figure 1)

3.1.2 Currently employed approximation to avoid overlap

To mitigate the impact of time-dependent productivity factors, the current approximation in TAG utilises a Euclidean distance-derived metric for ATEM within the econometric models. The approximation follows from the idea that since part of the productivity benefits of transport schemes arise from travel time savings, avoiding a time-dependent measure for estimation of the agglomeration elasticity would better approximate to an extraneous scale effect resulting from

[1] Venables, A. J. (2007). Evaluating urban transport improvements: cost–benefit analysis in the presence of agglomeration and income taxation. *Journal of Transport Economics and Policy (JTEP)*, *41*(2), 173-188.

market failures[2]. In broader terms, the GTC based ATEM is proxied here by the distance-based ATEM as distances are the main factor in GTCs[3].

Following from Venables (2007), the calculation of WEIs of agglomeration proceeds in two steps. In the first step, GTC based changes in economic density $(d\ \log \rho_i^{\bar{g}})$ are measured using transport models that predict changes in agglomeration based on changes in GTC $(\bar{g})$ caused by improvements in the transport network. For n zones indexed by $i, i = (1, \dots, n)$, or $j, j = (1, \dots, n)$, the measure of economic density (ρ_i) can take the form

$$\rho_i^{\bar{g}} = \sum_{j=1}^{n} m_j \cdot f(\bar{g}_{ij})$$

where m_j is a measure of economic mass at zone j and $f(.)$ is a decreasing function of the mean modal GTC $(\bar{g})$ of travelling from i to j.

In the second step, distance-based ATEM elasticities (η_{ω,ρ^d}) are estimated by employing the following measure of economic density

$$\rho_i^D = \sum_{j=1}^{n} \frac{m_j}{d_{ij}^{\alpha}}$$

where d_{ij} is the Euclidean distance between zones i and j and α is a parameter that determines the spatial decay of agglomeration impacts.

Using the two quantities described above, the WEIs of agglomeration induced by the transport scheme are computed as

$$d\ \log \omega = \sum_{i=1}^{n} \eta_{\omega,\rho^d} \times d\ \log \rho_i^{\bar{g}}$$

The question that arises here is: To what extent these calculations deliver effects that are solely induced by market failures? In other words, can distance-based agglomeration elasticities truly provide an unadulterated scale effect of the agglomeration externality?

Note that the generic econometric model used to derive agglomeration elasticities from disaggregate micro-level panel data (for workers or firms) takes the form

$$\omega_{ict} = g(\rho_{ct}) + f_{ct} + u_{it} + z_{it} + e_{ict}$$

where ω_{ict} is the productivity of worker or firm i in areas c at time t, ρ_{ct} is the ATEM of area c at time t, f_{ct} and u_{it} are unobserved area and firm effects, respectively, with both possibly correlated with ρ_{ct}, z_{it} signifies other measurable effects on productivity, and e_{ict} is a random error term.

The agglomeration elasticities derived from the estimated function $g(.)$ captures how productivity changes with ATEM, with all other factors kept constant. In other words, we desire the distance-based ATEM estimates to leave out any non-externality effects and isolate an elasticity that represents only the pure scale effect of agglomeration. The empirical literature on agglomeration routinely employs two approaches towards achieving this objective: (a) use of a combination of direct covariate adjustment and panel individual effects/ within estimation to adjust for observed and unobserved confounders, and (b) use of instrumental variables (IV) or control function (CF) based estimation to adjust for time-varying confounders, measurement error, or reverse causality.

[2] Graham, D.J. (2023). Potential overlap between agglomeration benefits and other elements of appraisal. Note to the DfT. London: DfT.
[3] Combes, P. P., & Lafourcade, M. (2005). Transport costs: measures, determinants, and regional policy implications for France. Journal of economic geography, 5(3), 319-349.

It is important to note that these approaches are not guaranteed to yield a pure externality effect, particularly, due to confounding bias from transport costs or time savings. More specifically, transport costs can vary systematically with ATEM and simultaneously influence productivity. As a result, both external and non-external attributes are consistently changing in the same direction - such as increasing - with ATEM, and they share a similar overall impact on productivity, such as generating gains. As the two attributes are highly correlated, it is exceeding challenging to differentiate the two sources of impacts empirically, leading to a problem of *observational equivalence*. The econometric model outlined above is prone to capturing non-external transport cost effects in the agglomeration elasticity due to omitted variable bias (OVB).

The above synthesis suggests that using a distance-based ATEM measure eliminates variability in travel times or costs when estimating the agglomeration elasticity, consequently lowering the likelihood of directly capturing productivity effects related to travel time in the elasticity. However, both external and non-external effects on productivity, which align with ATEM, exist, and observational equivalence complicates the separation of these effects. Therefore, it cannot be definitively asserted that distance-based productivity elasticities with respect to ATEM exclusively identify a pure externality scale effect.

Nevertheless, as Graham (2023) emphasise, the methodological challenges outline above are extremely complex to resolve, and minimising overlap would require a substantial overhaul of the fundamental approach employed to compute WEIs of agglomeration. Moreover, even with a redesign in approach, it will likely not be possible to eliminate overlap entirely while staying within the bounds of the partial equilibrium framework of TAG.

It is worth recognising that the recommendation to use distance-based elasticities is not widely appealing to practitioners as their use leads to an inconsistency between outputs of transport models and inputs of the econometric models of agglomeration. Thus, the next crucial question is: Under what conditions is it possible econometrically to have a time-based measure of agglomeration (for instance, GTC-based) in the equation and not double count?

Note that, a GTC-based measure of ATEM calculated using panel data, by the virtue of its construct, captures spatio-temporal variances in travel time and costs resulting from differences in travel conditions and the quality and volume of infrastructure. As a result, when transport interventions are made, their effects will show up in the GTC-based ATEM measure. As explained in Section 1, transport interventions can generate productivity effects via both business travel time savings (DUBs) and agglomeration effects (WEIs). Using a GTC-based measure of ATEM to compute agglomeration elasticity will consequently encompass a blend of these two effects, making it unfeasible to separate them. Therefore, employing this elasticity in appraisal is discouraged as it will inevitably result in double counting.

Graham (2006)[4] showed that use of a GTC based measure of ATEM delivers larger agglomeration elasticities than a distance-based ATEM, primarily, because the former captures spatiotemporal variances in both travel costs and distance. However, the result does not necessarily demonstrate that the distance-based ATEM measure isolates an externality effect. Rather, it just signifies capturing of the DUBs productivity effects in the GTC based agglomeration elasticity. Therefore, as Graham (2023) recommend, to validly use GTC based elasticities in appraisal, a change in the fundamental approach used to calculate WEIs of agglomeration is required.

Compared to the empirical issues discussed above, adjustments for spatial self-selection are more straightforward to apply. In wage models of agglomeration, such adjustments can be done via a combination of direct covariate adjustment and use of panel individual effects/ within estimation. The approach leverages the wealth of information on workers and their skills as contained in micro panel datasets.

Adjustment for skills in assessing the impacts of agglomeration on productivity enables differentiation between productivity variances solely due to density differences and those resulting from the allocation of workers with varying skill levels across different locations. Expanding on this

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[4] Graham, D. J. (2006). Wider economic benefits of transport improvements: link between agglomeration and productivity. Stage 2 Report. London: DfT.

notion, panel datasets on workers can also be utilised to gauge the extent to which individual productivity shifts when transitioning from low to high density areas. This approach further aids in effectively managing the geographical sorting of workers with different skill levels.

The research commissioned by the Northern Way from the Spatial Economics Research Centre (SERC) at the London School of Economics[5] adopts the above approach whilst estimating agglomeration elasticities for the UK using micro panel wage data from the Annual Survey of Hours and Earnings (ASHE). The study discusses the issue of endogeneity via 'sorting' in terms of a 'people versus place' distinction, arguing that if skilled workers are attracted to the largest cities, then a productivity gradient will be observed due to a 'people' effect, even in absence of 'place' based agglomeration effects. The study emphasises the importance of adjusting for heterogeneity in labour quality to obtain a reliable estimate of the pure effect of agglomeration on wages. To address sorting the authors adjust for people effects by including detailed information on worker characteristics (that is, age, gender, education, occupation – public or private sector, full-time or part-time, and subject to a collective pay agreement of not, and industry) within their wage model as well as worker level fixed effects.

In TFP models of agglomeration, adjustments to sorting are made indirectly by allowing for unobserved heterogeneity in productivity across firms while attributing a part of it to differences in factor quality. Such unobserved heterogeneity can then be adjusted by adopting an estimation based on panel instrumental variables (IV) or the panel control function (CF) approach, as in Graham et al. (2009)[6], for instance.

Annex A.2 summarises known data sources which the future researcher might want to consider for the development of wage or productivity models.

3.1.3 Reformulating the econometric model of agglomeration

In response to Graham (2023), Cheyney and Stead (2023)[7] suggested exploring a zone-level model of the form

$$\Delta productivity_{it} = \gamma_i + \gamma_t + \beta_1 \sum_j \left(\left(\frac{trips_{ijt-1}}{emp_{it-1}} + \frac{trips_{ijt-1}}{emp_{it-1}} \cdot 0.5 \cdot \left(\frac{GTC_{ijt}}{GTC_{ijt-1}} \right)^{eGC} \right) \cdot \Delta GTC_{ijt} \right)$$

$$+\beta_2 \sum_j \left(\frac{\Delta trips_{ijt}}{emp_{it-1}} \cdot GTC_{ijt}{}^{\alpha} \cdot employment_{jt}{}^{\theta} \right),$$

where zonal productivity effects resulting from cost savings (DUBs) and from changes in effective density (agglomeration externalities) are estimated together. The suggested model is worth further attention, in particular, because the associated data requirements are relatively undemanding. The time series of OD travel flow (trips) matrices and GTCs required to calibrate the above model can be generated from mobile network datasets.

Nevertheless, it is worth noting that the suggested model considers zones as the entity of production, while, in reality, zones are not units of production and thus do not exhibit optimising behaviour within a given market structure. Rather it is the firms within the zones that are. A more theoretically founded approach would therefore comprise of estimating a firm level production function, aggregating to zones taking an expectation and then carrying out a second stage econometric model to compute agglomeration effects.

Relatedly, if firms are transport users themselves, then their DUBs may coincide with agglomeration externalities, it may be worth exploring the addition of firms' transport demand into

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[5] Overman, H. G., Gibbons, S., D'Costa, S., Mion, G., Pelkonen, P., Resende, G., & Thomas, M. (2009). Strengthening economic linkages between Leeds and Manchester: feasibility and implication. Full Report. London: SERC.

[6] Graham, D. J. (2009). Identifying urbanisation and localisation externalities in manufacturing and service industries. Papers in Regional Science, 88(1), 63-84.

[7] Cheyney, C., & Stead, I. (2023). Agglomeration Econometrics: Adding travel volumes and isolating externalities Note to the DfT. London: DfT.

their production function. In other words, we have a production function where transport enters explicitly as a factor of production, in addition to labour, materials, capital and other inputs.

The caveat here is that we have good measures of firm's labour and material demand and we can estimate their capital, however, we do not necessarily know their transport demands. It is worth considering whether there are data that would allow transport to be represented as an input that enters explicitly into the production function and then separate out the productivity effects that result from firms' direct use of transport from those due to the externality. One way of approaching this problem could be to use transport infrastructure as an input factor[8].

3.1.4 Conclusions and recommendations

The key points made in this section are as follows.

- The evaluation of impacts in Cost-Benefit Analysis (CBA) adheres to the principle of additionality, which requires distinct impacts and groups of impacts considered in the assessment to be non-overlapping. This fundamental principle forms the basis of the DfT TAG method for appraisal.
- Overlap between TAG Level 1 direct welfare effects and TAG Level 2 wider economic impacts of agglomeration can arise due to the influence of time-dependent productivity effects arising from reduction in GTCs.
- The use of a distance-based ATEM measure removes variance in GTCs when estimating the agglomeration elasticity, thereby reducing potential for direct capture of travel time productivity effects in the elasticity. Nevertheless, the simultaneous existence of externality and non-externality effects on productivity which scale with ATEM makes it challenging to empirically distinguish the two effects due to observational equivalence. Therefore, distance-based elasticities of productivity with respect to ATEM do not necessarily guarantee identification of a pure agglomeration externality effect.
- By design, the GTC-based ATEM measure captures spatiotemporal variances in travel times and costs. Therefore, without a change in the fundamental approach used to calculate WEIs of agglomeration, the use of GTC based elasticities will definitively result in double counting because econometric estimation of GTC elasticities cannot isolate productivity effects of agglomeration from DUBs generated from time savings.
- It is also important to net out dynamic (Level 3) WEIs of agglomeration arising due to spatial sorting and relocation of firms and workers by productivity from static (Level 2) WEIs. In wage models, this can be achieved via a combination of direct covariate adjustment and use of worker-specific fixed effects. In TFP models, these can be adjusted by adopting an estimation based on instrumental variables (IV) or control function (CF).
- With respect to reformulating the econometric model of agglomeration, a zone-level productivity model that estimates both the productivity effects resulting from cost savings (DUBs) and from changes in effective density (agglomeration externalities) within the same regression is certainly appealing and worthy of further investigation. However, because zones are not the primary units of production, rather the firms within are, the implicit choice of boundaries in zonal models requires attention.
- As the most severe double-counting threat arises from firms being transport users themselves, it is worth exploring the addition of transport explicitly as a factor of production, in addition to labour, material, capital and externalities. This approach could allow separating the productivity effects that result from firms' direct use of transport from those due to the externality.

[8] See for example, Rietveld, P., & Nijkamp, P. (1992). Transport and regional development.

The section concludes with the following recommendation for future work.

R1 Double-counting concerns should be addressed by redesigning the fundamental approach to calculate WEIs of agglomeration. For this purpose, a zone-level productivity model in which productivity effects arising from both cost savings and agglomeration externalities are estimated together is worthy of investigation.

3.2 Distinction between urbanisation and localisation

R2	**Recommendation: There is a need for theoretical/ conceptual work on the distinction between urbanisation and localisation effects as a necessary precursor to developing empirical solutions for appraisal. Accordingly, models that differentiate between these effects should be estimated to assess whether the resulting evidence is appropriate for utilisation in appraisal.**

There is continued interest in the distinction between urbanisation and localisation economies. This distinction been extensively employed in theoretical literature over an extended period. Localisation economies are intra-industry; they are external to firms but internal to the industry. Urbanisation economies are cross-industry; they are external to the firm and the industry but internal to cities.

3.2.1 Theoretical differentiation

Localisation economies, also known as Marshallian economies of scale[9], refer to the efficiency improvements resulting from the increased size of a specific industry operating in close proximity. These benefits are believed to stem from three primary sources. Firstly, geographic proximity enhances communication, facilitating the exchange of technological knowledge among firms within the same industry. Secondly, the clustering of industries can lead to the effective supply of intermediate inputs with greater diversity and at reduced costs due to the expansion of related trades. Thirdly, firms can access larger markets for both inputs and outputs, and especially benefit from shared access to a skilled local labour force.

Urbanisation economies, also referred to as Jacobian externalities[10], describe the productivity benefits that firms gain by being situated in densely populated areas like cities. Firms enjoy advantages stemming from the size of markets, the closeness of market areas for exchange of inputs and outputs, and the availability of quality infrastructure and public services.

3.2.2 Identifying urbanisation and localisation economies in practice

In theory, it is possible to distinguish impacts generated via localisation or urbanisation economies. For sector $s,\ s = (1, \dots, S)$ in zone i, localisation (ρ_i^s) and urbanisation (ρ_i^U) can be represented empirically using employment data E, or some other measure of industry size, say, by the ATEM variables

$$\rho_i^s = \frac{1}{n}\sum_{j=1}^{n} E_{sj} f\left(d_{ij}\right)$$

$$\rho_i^U = \frac{1}{n}\sum_{j=1}^{n}\sum_{s=1}^{S} E_{sj} f(d_{ij})$$

where $f(d_{ij})$ is an appropriate impedance function. Accordingly, if an econometric model can deliver separate elasticities with respect to urbanisation (η_{ω,ρ^s}) and localisation (η_{ω,ρ^U}) estimated within the same model, the two-step productivity calculations described in Section 3.1 can be expanded to introduce this distinction.

[9] Marshall, A. (1890). Principles of economics, by Alfred Marshall. Macmillan and Company.
[10] Jacobs, J. (1969). 'The Economy of Cities', Random House, New York, NY.

Nevertheless, it is anticipated that localisation and urbanisation ATEMs will exhibit correlation since the concentration of industries and urban areas typically coincide. Table 3 illustrates the correlation coefficients, Cor (U, L), between the urbanisation ATEMs and localisation ATEMs calculated for various SIC sections in the UK.

Alongside, the variances of the urbanisation ATEMs and localisation ATEMs, Var (U) and Var (L), respectively, and their covariances, Cov (U, L), are also summarised in this table. The values in this table have been calculated using the 2011 data on annual employment levels in each Middle Layer Super Output Area (MSOA), obtained from the Business and Employment Register available at Nomis.

Table 3: Correlation between urbanisation and localisation ATEMs for different SIC sections

SIC Section	Cor (U, L)	Cov (U, L)	Var (U)	Var (L)
A: Agriculture, forestry, and fishing	0.752	0.162	439.856	0.000
B: Mining and quarrying	0.094	0.124	439.856	0.004
C: Manufacturing	0.586	10.253	439.856	0.695
D: Electricity, gas etc	0.683	0.886	439.856	0.004
E: Water supply	0.885	1.422	439.856	0.006
F: Construction	0.963	12.705	439.856	0.396
G: Wholesale and retail	0.980	53.573	439.856	6.800
H: Transportation and storage	0.957	17.193	439.856	0.734
I: Accommodation and food	0.991	33.600	439.856	2.616
J: Information and communication	0.970	37.358	439.856	3.372
K: Financial and insurance	0.927	34.464	439.856	3.144
L: Real estate	0.983	11.768	439.856	0.326
M: Professional, scientific, and technical	0.977	65.811	439.856	10.324
N: Administrative and support service	0.996	46.937	439.856	5.053
O: Public administration and defence	0.972	18.054	439.856	0.785
P: Education	0.983	32.484	439.856	2.484
Q: Human health and social work	0.979	40.79	439.856	3.949
R: Arts, entertainment, and recreation	0.992	11.416	439.856	0.301
S: Other service activities	0.993	10.805	439.856	0.269

Source: analysis of 2011 data from the Business and Employment Register, Nomis.

The table indicates that in most economic sectors, there is a strong correlation between the localisation and urbanisation ATEMs, which is likely to lead to issues related to multicollinearity. In fact, previous empirical studies that have attempted to distinguish localisation and urbanisation elasticities within the same model have found limited success as problems of collinearity tend to adversely affect these models. For instance, Nakamura (1985)[11] estimated the effect of localisation economies on the productivity of 20 manufacturing industries. They find an unweighted average elasticity of productivity with respect to industry size of 0.05 and an average city size elasticity of 0.03. They conclude that the effects of localisation tend to be more significant than those of urbanisation. Henderson (1986)[12] also finds weak evidence of urbanisation economies using industry level data for US MSAs and Brazilian cities but does find positive localisation economies.

[11] Nakamura, R. (1985). Agglomeration economies in urban manufacturing industries: a case of Japanese cities. Journal of Urban economics, 17(1), 108-124.

[12] Henderson, J. V. (1986). Efficiency of resource usage and city size. Journal of Urban economics, 19(1), 47-70.

Relatedly, Combes and Gobillon (2015)[13] point out that own industry mass should be removed from the computation of the urbanisation measure as own industry effects have already been introduced in the specification via the localisation measure. However, they do note that when the number of industries is large, the correlation between the urbanisation measures computed with and without exclusion of the own industry mass is large. Monseny et al. (2013)[14] adopt this approach to estimate urbanisation and localisation economies in the manufacturing industry in Spain. However, while the reported urbanisation and localisation elasticities from the study are quite similar in magnitude, the latter effects are found to be more significant compared to the former.

Graham (2009)[15] tried to overcome the multi-collinearity issue by generating measures of localisation and urbanisation expressed in different units. They use a measure of urbanisation that captures the scale and proximity of economic mass that is accessible from any location. This measure is similar to the ATEM measure introduced above. However, to measure localisation, they introduce a measure based on distance bands rather than market potential. In particular, the distance-band localisation variables are not explicitly expressed as densities, but in terms of the sum of employment found within a given catchment area over some defined radius taken from the centroid of zone i. The underlying idea is to have a measure of localisation that is more sensitive to the micro-scale over which these effects are present. However, even with these adjustments, they show evidence of problems of identification in estimating distinct urbanisation and localisation effects for highly urbanised sectors of the economy.

Interestingly, Duranton and Puga (2004)[16] theoretically demonstrate that there are significant parallels in the benefits experienced by firms operating within specific industries and those engaging in interactions across industries. In essence, they argue that the fundamental underpinnings of agglomeration support the presence of both types of externalities. If indeed urbanisation and localisation share similar origins and outcomes, a key implication for quantitative research is the challenge in distinguishing between individual effects. In fact, the empirical studies reviewed above suggest that there may be lack in sufficient variation in the data to identify the two effects separately. In particular, the two variables are not just highly correlated, but they also have the same general effect on productivity, thus, leading to an issue of observational equivalence.

To deal with this issue of observational equivalence, another stream of studies has attempted to distinguish urbanisation effects from those of localisation using indices of relative-diversification and relative-specialisation to represent urbanisation and localisation, respectively. The underlying motivation is to capture two different mechanisms: the relative-specialization index signifies the role of the industry local share while the relative-diversity determines the relevance of the distribution of employment over all other industries. For instance, consistent with the approach laid out in Combes and Gobillon (2015), Tao et al. (2019)[17] study agglomeration economies in creative industries in China using the indices

$$Specialisation_{it} = \frac{E_{sit}/E_{it}}{\sum_{j=1}^{n} E_{sjt}/\sum_{j=1}^{n} E_{jt}}$$

$$Diversity_{it} = \frac{1}{\sum_{j=1}^{n}\left(\frac{E_{sjt}}{\sum_{j=1}^{n} E_{sjt}}\right)^2}$$

alongside a total population-based measure of density and controls for firm size, ownership, and industry concentration. As Combes and Gobillon (2015) suggest, inclusion of firm size controls for

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[13] Combes, P. P., & Gobillon, L. (2015). The empirics of agglomeration economies. In Handbook of regional and urban economics (Vol. 5, pp. 247-348). Elsevier.

[14] Jofre-Monseny, J., Marín-López, R., & Viladecans-Marsal, E. (2014). The determinants of localization and urbanization economies: Evidence from the location of new firms in Spain. Journal of Regional Science, 54(2), 313-337.

[15] Graham, D. J. (2009). Identifying urbanisation and localisation externalities in manufacturing and service industries. Papers in Regional Science, 88(1), 63-84.

[16] Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In Handbook of regional and urban economics (Vol. 4, pp. 2063-2117). Elsevier.

[17] Tao, J., Ho, C. Y., Luo, S., & Sheng, Y. (2019). Agglomeration economies in creative industries. Regional Science and Urban Economics, 77, 141-154.

the effect of competition in local input and non-tradable goods market. It also representative of the firms' ability to internalise part of the local effects, particularly those related to knowledge spillovers. The third control variable captures the unevenness of the distribution of industries over space. They find statistically significant urbanisation economies, but no significant impact of localisation.

Similar conclusions were drawn by Cheng et al. (2023)[18] and Malmberg et al. (2000)[19] who apply this approach to study the impact of agglomeration externalities on urban green total-factor productivity in China and on the export performance of Swedish firms, respectively. Conversely, Guo and He (2016)[20] and Renski (2010)[21] find localisation economies to be more significant in the context of predicting entrepreneurship in China and the survival of new, independent business establishments in the continental United States, respectively. Nevertheless, Anderson et al. (2005)[22] find both effects to be statistically significant in understanding the spatial distribution of commercial patents in Sweden.

Given the mixed success of the relative-diversification and relative-specialisation indices, it may be worth reconsidering whether the urbanisation and localisation effects are actually theoretically distinguishable.

3.2.3 Implications for transport appraisal

In the context of transport appraisal, Graham and Gibbons (2019)[23] further highlight that it is extremely hard to find a scenario where a transportation intervention changes localisation without also affecting urbanisation. Thus, treating these effects as distinct additive components rather than incorporating them into a comprehensive agglomeration term may not yield any substantial additional understanding. Under the above-described conditions of observational equivalence-cum-multicollinearity, estimation with a single agglomeration ATEM variable may be preferred as it will likely capture the combined effect up to a certain extent. This is demonstrated via a simple example below.

Suppose the true productivity model is

$$Y = a + b_1 U + b_2 L + e,$$

where, Y is the output, U and L represent the urbanisation and localisation variables, and e signifies the error. b_1 and b_2 are the parameters of interest capturing the effect of urbanisation and localisation, respectively, on productivity. Instead of the true model, the analyst estimates the model

$$Y = a + b_1 U + v,$$

where, v represents the new error term. We then have,

$$E\left(\widehat{b_1}\right) = b_1 + b_2 \times \frac{Cov(U, L)}{Var\ (U)}.$$

Note that due to the omitted variables bias (OVB), our estimate of b_1, that is, $\widehat{b_1}$ partly captures a combined effect of b_1 and b_2. Based on the data on the variances of the urbanisation ATEMs, Var (U), and the covariances between urbanisation and location ATEMs, Cov (U, L), as summarised in Table 3, it can be noted that for highly urbanised industry sectors such as finance and information

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18 Cheng, Z., Li, X., Zhu, Y., & Wang, M. (2023). The effects of agglomeration externalities on urban green total-factor productivity in China. Economic Systems, 47(2), 101025.

19 Malmberg, A., Malmberg, B., & Lundequist, P. (2000). Agglomeration and firm performance: economies of scale, localisation, and urbanisation among Swedish export firms. Environment and Planning a, 32(2), 305-321.

20 Guo, Q., He, C., & Li, D. (2016). Entrepreneurship in China: The role of localisation and urbanisation economies. Urban Studies, 53(12), 2584-2606.

21 Renski, H. (2011). External economies of localization, urbanization and industrial diversity and new firm survival. Papers in Regional Science, 90(3), 473-502.

22 Andersson, R., Quigley, J. M., & Wilhelmsson, M. (2005). Agglomeration and the spatial distribution of creativity. Papers in Regional Science, 84(3), 445-464.

23 Graham, D. J., & Gibbons, S. (2019). Quantifying Wider Economic Impacts of agglomeration for transport appraisal: Existing evidence and future directions. Economics of Transportation, 19, 100121.

and communication technology, the estimated effect of, $E(\widehat{b_1})$, captures roughly 10 percent of the localisation effects due to the OVB. For less urbanised sectors such as manufacturing, this percentage is roughly 3. These calculations suggest that 3-10 percent of the localisation effects are already captured within urbanisation effects due to OVB.

It is worth noting that while the current TAG practice does not distinguish urbanisation and localisation effects, a sectoral decomposition of urbanisation effects is already applied. This in a way constitutes examining the role of local industrial structure. On this note, Graham and Gibbons (2019) also rightly suggest exploring concentrations based on functional characteristics as industrial classifications may not be the most effective way of defining concentrations of similar firms.

3.2.4 Conclusions and recommendations

The key points made in this section are as follows.

- In theory, urbanisation and localisation effects can be separately represented using urbanisation and localisation ATEM variables and estimating the two elasticities within the same econometric model.
- However, in practice, it is difficult to disentangle the two effects because not only are the two variables highly collinear, but they also have the same effect on productivity, leading to a problem of equivalence of outcomes.
- Moreover, from Duranton and Puga (2004), it is known that the urbanisation and localisation share the same origins and outcomes. Therefore, it is also worth exploring whether the distinction between the two effects is theoretically well-founded.
- Further, as Graham and Gibbons (2019) highlight, any transport intervention is unlikely to alter localisation without simultaneously altering urbanisation or vice-versa. Thus, viewing these two effects as independent additive components rather than integrating them into a broader agglomeration term may not offer any significant additional insights.

The section concludes with the following recommendation for future work.

R2 There is a need for theoretical/ conceptual work on the distinction between urbanisation and localisation effects as a necessary precursor to developing empirical solutions for appraisal. Accordingly, models that differentiate between these effects should be estimated to assess whether the resulting evidence is appropriate for utilisation in appraisal.

3.3 Amenity effects and wider relocation costs

R3 Recommendation: Incorporating consumption and amenity externalities in partial equilibrium transport appraisal is an outstanding task on the research agenda. A future research project should define the empirical estimates (for instance, a price index elasticity or location attractiveness elasticity) that such a partial equilibrium approach requires, and develop a narrative and the associated proofs that address the double counting concern in case of this type of externality.

The previous subsections covered agglomeration economies related to firm productivity. Intuition and a growing body of empirical evidence suggests that not only firms are affected by improved accessibility: effective economic density may also translate into amenities (or dis-amenities) that make urban areas more (or less) attractive for workers and residents.

Based on these premises, it is a natural question whether at least a part of the change in amenity levels are separate from the net benefit directly perceived by transport users and thus the associated economic spillovers should be accounted for in transport appraisal.

3.3.1 Definitions

The spatial economic literature distinguishes two broad groups of consumption-side agglomeration economies that are relevant and will be defined separately in this report.

The first group includes positive *consumption externalities* which arise because urban density enables residents to consume a greater variety of non-tradable goods and services at lower prices. When non-tradable services must be consumed where they are produced, but transport is costly within a city, households have an incentive to locate close to service providers. By improving access to a location where consumption takes place, the range of locally available services increases and prices may also fall due to spatial competition.

Based on the underlying market structure (monopolistic competition) and its mathematical representation, this channel of agglomeration is similar to the WEI stemming from imperfect competition, which is included in TAG already. However, the latter refers to imperfect competition in tradable goods and services that households consume at their residential location. Consumption externalities are somewhat different in the sense that they capture access to the place where non-tradable goods and services are consumed by households that may not live where consumption takes place.

Glaeser et al. (2001)[24] attribute the rise of consumption-centric urban cores to this mechanism. From a partial equilibrium perspective, greater product variety and lower monopoly mark-ups can be considered as an externality as residents who do not use transport services may also perceive some of the associated benefits. At the same time, a double counting concern is present in this channel of agglomeration because at least a fraction of transport users may enjoy these benefits. Their willingness to pay for transport services captures the fact that their utility from consumption increases with their ability to travel to high-density destinations.

So, in effect, the value of travel time savings (VTTS) and direct user benefits for non-work trips may partially double count these economic gains. Note the parallels of this concern with the matching benefits of firm productivity externalities. In the context of TAG, the extent of overlap of direct and amenity benefits captured in the specified VTTS might be limited.

The stated preferences study underlying the estimation of VTTS values controls for geographical factors (e.g. urban/rural type of origin or destination) in transport users appreciation of time savings, finding only a very small minority of geography controls to be statistically significant: variations in VTTS '*by geography are generally explained by variations in trip and socio-economic characteristics*'[25]. As a result, while double counting might exist, time savings based on the VTTS as they are currently estimated are unlikely to capture the attractiveness of increased amenities related to land use changes as a consumer benefit.

The second group can be labelled as *amenity spillovers*. This agglomeration mechanism reflects the fact that the attractiveness of urban locations for residential and other activities may depend on the surrounding economic density irrespective of the local price and diversity of consumption possibilities. For example, public spaces in dense urban areas may be equipped with more advanced facilities such as street lighting, paved roads and pedestrian infrastructure, and other amenities. Meanwhile, they may lack other amenities, for example extensive green space, clean air, etc. This makes the sign of such externalities ambiguous.

Moreover, proximity to others increases the possibility and quality of human interactions which may affect wellbeing. This phenomenon is similar to knowledge spillovers, one of the well-known micro-foundations of the productivity literature, but it relates to non-work activities. The perceived amenity stemming from urban density is likely heterogeneous among urban residents. Some individuals may experience discomfort as a result of a dense built environment and frictions with others. Therefore, again, the net value of amenity spillovers is not necessarily positive.

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[24] Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of economic geography*, *1*(1), 27-50.

[25] Arup, ITS Leeds, and Accent for the DfT (2015). Provision of market research for value of travel time savings and reliability. Phase 2 Report, p. 236 – available at https://assets.publishing.service.gov.uk/media/5a7ffa11ed915d74e622bbe3/vtts-phase-2-report-issue-august-2015.pdf.

Based on these definitions, Section 2.3.2 covers the existing empirical evidence while Section 2.3.3 reviews existing models that can serve as a basis for incorporating amenity effects in the economic framework of transport appraisal.

3.3.2 Empirical evidence

Our review of the literature estimating the consumption value of agglomeration suggests that direct empirical evidence on this theme remains scarce. This view echoes Ahlfeldt and Pietrostefani (2019)[26] who state that “the literature on consumption benefits arising from agglomeration is underdeveloped relative to the production side” (pp 45, Section 4.5 of Appendix A1). One of the first attempts come from Couture (2016)[27] who provide an estimate of the gains from variety in the US restaurant industry. Using travel data and detailed online microgeographic data on local businesses available via Google Places, Couture (2016) developed a framework to identify an individual’s willingness to pay for access to a preferred location from the extra travel costs that they incur to reach it.

Based on their estimates, Couture (2016) calculated the corresponding aggregate welfare gains from product variety in the US restaurant industry to be approximately 2% of consumer expenditures on travel. A major limitation of Couture (2016)’s approach is that they take as given both the location of the origin of trips and the set of destinations, whereas density matters partly because it changes the set of potential venues and, as a result, possibly alters the choice of residential location.

More recent attempts to measure the consumption benefits of agglomeration such as Ahlfeldt et al. (2015)[28] and Miyauchi et al. (2021)[29] are based on spatial general equilibrium models that are described in the next sub-section.

In another recent study, AitBihiOuali (2022)[30] calculated the amenity benefits of cities in the Midlands and the North of England. Building upon the theoretical framework of Glaeser et al. (2001), AitBihiOuali (2022) suggested that at spatial equilibrium, the valuation for urban amenity can be expressed as the difference between urban rents and urban wages. The adopted approach is also in line with Roback (1982).[31] The estimated elasticity with respect to density is 0.109.

However, such valuations comprise other impacts of agglomeration including innovation, decreased travel speeds due to congestion, and reduced pollution and energy use, that are already partly captured in TAG and, therefore, creates a highly credible threat of double counting impacts. For a detailed list of impacts of agglomeration, see Ahlfeldt and Pietrostefani (2019).

3.3.3 Economic models of amenity/consumption benefits and their compatibility with appraisal

The review of the literature suggests that combining traditional productivity externalities with consumption externalities has been an open challenge in recent years and Moon (2022)[32] is likely the first attempt that achieved that.

Moon (2022) develops a spatial general equilibrium model based on Anas and Kim (1996)[33] and Lucas and Rossi-Hansberg (2002)[34] with the following features. (i) Households consume a variety

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[26] Ahlfeldt, G. M., & Pietrostefani, E. (2019). The economic effects of density: A synthesis. *Journal of Urban Economics*, 111, 93-107

[27] Couture, V. (2016). Valuing the consumption benefits of urban density. University of California, Berkeley, Working Paper.

[28] Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica*, *83*(6), 2127-2189.

[29] Miyauchi, Y., Nakajima, K., & Redding, S. J. (2021). The economics of spatial mobility: Theory and evidence using smartphone data (No. w28497). National Bureau of Economic Research.

[30] AitBihiOuali, L. (2022). Effects of population density changes on the value of amenities in the United Kingdom: Evidence from the Rail Plan for the Midlands and the north of England. National Infrastructure Commission: UK.

[31] Roback, J. (1982). Wages, rents, and the quality of life. *Journal of political Economy*, *90*(6), 1257-1278.

[32] Moon, Y. S. (2022). Internal structure of consumer cities: Core and subcenters. *Journal of Regional Science*, 62(5), 1250-1273.

[33] Anas, A., & Kim, I. (1996). General equilibrium models of polycentric urban land use with endogenous congestion and job agglomeration. *Journal of Urban Economics, 40*(2), 232-256.

[34] Lucas, R. E., & Rossi–Hansberg, E. (2002). On the internal structure of cities. *Econometrica, 70*(4), 1445-1476.

of both tradable and non-tradable goods. (ii) The production of urban goods involves agglomeration (urbanisation) economies, so firms have an incentive to cluster in close locations within the city. (iii) Households must travel in a congestible transport network to access non-tradable services. They have an incentive to form dense residential areas close to the producers of non-tradables because this allows them to access a greater variety.

Moon (2022) explores the impact of the strength of the two agglomeration forces on urban spatial structure. This model would be suitable to compute the welfare effect of transport improvements in the presence of consumer externalities but the paper's focus remains on urban form.

Would it be possible to turn Moon's model into a structure similar to Venables (2007), which provided the primary justification for the calculation of productivity benefits in TAG? There is no trivial solution in this respect. The key simplifying assumption of Venables (2007) is that urban production takes place in one location (the 'CBD'). Due to perfect competition in the production and labour markets, any improvement in productivity is capitalised in wages. In his setup total labour supply increases proportionally with the city boundary and thus the commuting distance. Welfare effects stemming from household and firm relocation, and imperfect competition, are muted in his model.

This set of assumptions turned out to be acceptable in light of the monocentric city tradition in urban economics. By contrast, consumption externalities assume love of variety in the location of consumption and the main channel through which agglomeration benefits households is an increase in variety. Thus, the monocentric city model is not suitable to capture this externality.

An appraisal-oriented economic model that is more tractable than Moon (2022) requires significant research efforts, and even if that investment is made, compatibility with TAG's partial equilibrium framework cannot be guaranteed.

Ahlfeldt and Pietrostefani (2019)[35] introduce a potential shortcut to the calculation of consumption externalities in the appendix of their paper. They derive amenity gains by multiplying household expenditure on non-tradable services in a city by the elasticity of the price index of restaurant services with respect to ATEM, given the aforementioned estimate of Couture (2016). More specifically, they caution that a part the elasticity of the price index may double count the reduced cost of car trips, a DUB. They refer to Couture (2016) who claims that 56% of the price index gains are pure gains from variety. Therefore, they multiply the price index elasticity by 0.56 to avoid double counting. From a theoretical point of view, this method is no more than a back-of-the-envelope calculation based on partial empirical evidence (Couture observes the price index of restaurants only). More fundamental research is needed to clarify the compatibility of this calculation method even with the general equilibrium framework of Moon, not to mention the partial equilibrium approach of TAG.

Let us now turn to the second group of externalities. Amenity spillovers were measured as well as predicted for counterfactual policy scenarios in quantitative urban models, an emerging literature hallmarked by Ahlfeldt et al. (2015)[36] and a series of follow-up papers. Quantitative urban models are spatial general equilibrium models in which households' decisions on residential and workplace locations are endogenous.

Ahlfeldt et al. define the attractiveness (amenity) of discrete locations as a numerical variable that can be quantified using observed economic outcomes such as commuting patterns and the spatial distribution of wages and floorspace prices. Then they decompose the location-specific amenity levels into a part that can be explained by access to economic mass and a location fundamental determined by geographical characteristics. This approach offers a suitable structural method to estimate the elasticity and distance decay of amenity externalities and then apply the model in the appraisal of counterfactual policy scenarios.

However, as mentioned above, quantitative urban models feature general equilibrium as opposed to the partial equilibrium framework of TAG. The contribution of amenity spillovers to welfare is not

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[35] Ahlfeldt, G. M., & Pietrostefani, E. (2019). The economic effects of density: A synthesis. *Journal of Urban Economics*, 111, 93-107

[36] Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica, 83*(6), 2127-2189.

additively separable because household utility is a nonlinear (multiplicative) function of the amenity value. This means that, using this model, one cannot prove that a partial equilibrium application of the estimated elasticity is free from the double counting concern.

3.3.4 Wider relocation costs

Transport projects can have an impact on government costs related to land use changes, specifically in the form of enabling infrastructure costs. As improvements to transport connectivity make development more attractive in specific locations, transport projects ultimately are likely to influence the location of where development happens. It is often the case, as observed in cities, that public transport connectivity might enable more brownfield development through densification, compared to a do nothing scenario where development would have been more spread out and likely to take place in greenfield locations.

In addition to this, there is evidence to suggest that greenfield development has higher associated enabling infrastructure costs compared to brownfield development. For instance, evidence from Trubka et al (2010)[37] shows that urban redevelopment costs tend to be lower compared to greenfield development costs. As a result, as these costs are born by government, changes in the type of development as a result of transport projects are likely to have an impact on enabling infrastructure costs and therefore total government costs, which could be referenced as "wider relocation costs".

In terms of how this can be applied to existing TAG appraisal frameworks, we can assume that any changes to government costs are a direct consequence of land use changes and that these do not have an impact on any other agglomeration mechanisms or dynamics. In reality, in a general equilibrium model, the government might choose to reallocate cost savings to other sectors, but this is not considered at this stage.

As a result, this impact could be considered additional and therefore incorporated as a new benefit to the appraisal framework if dynamic agglomeration and urban densification can be demonstrated. In order to calculate these benefits, land use change by type (brownfield and greenfield) would have to be estimated in the do something scenario (in units of development) compared to a do nothing scenario and multiplied by a benchmarked enabling infrastructure cost figure per dwelling or unit of development to calculate the total benefit. Note that development may be higher in the do something scenario, unless a 100% displacement of development is assumed in the do something scenario compared to the do nothing scenario.

3.3.5 Conclusions and recommendations

We reach the following conclusions on the current state of knowledge on the amenity externality of transport-induced economic densification.

- A small but growing number of studies provide empirical evidence on the existence of a link between access to economic mass and consumption/amenity benefits (and costs) in an urban environment. Such benefits may emerge through variety in non-tradable services in accessible locations, public goods unlocked by a dense built environment, the high frequency of human interaction, and potential nuisance factors associated with density.
- At the same time, empirical evidence on the amenity effect of transport improvements specifically is scarce in the same literature.
- Two prototype studies show that both consumption and amenity externalities can be encapsulated in general equilibrium models such that this channel is included in the calculation of the welfare effect of a transport policy. However, these general equilibrium effects are not directly compatible with TAG.

[37] Trubka, R., Newman, P., & Bilsborough, D. (2010). The costs of urban sprawl–Infrastructure and transportation. *Environment Design Guide*, 1-6. Royal Australian Institute of Architects.

- Fundamental research needs to be performed to prove that consumption and amenity externalities can be quantified in the partial equilibrium appraisal method of TAG without double counting.
- Spatial general equilibrium models can deliver elasticities of amenity value with respect to access to economic mass. However, the contribution of amenity spillovers to welfare is not additively separable. Therefore, application of these elasticities in partial equilibrium framework of TAG may lead to double counting of impacts.

The section concludes with the following recommendation for future work.

R3 Incorporating consumption and amenity externalities in partial equilibrium transport appraisal is an outstanding task on the research agenda. A future research project should define the empirical estimates (for instance, a price index elasticity or location attractiveness elasticity) that such a partial equilibrium approach requires, and develop a narrative and the associated proofs that address the double counting concern in case of this type of externality.

4. Empirical methods, specifications, and their validation

4.1 Contributions from different 'micro-mechanisms'

R4	**Recommendation: Contributions from distinct micro-mechanisms of agglomeration (sharing, matching, and learning) should be estimated via models that exploit natural experiments where enough variation in the contributions can be guaranteed with some of the micro-mechanisms kicking in and some not. Consideration should be given as to whether the resulting evidence is suitable for**

While there are abundant studies assessing the overall impact of agglomeration on productivity, there has been some recent interest in disentangling the contributions from different micro-mechanisms of agglomeration: sharing, matching, and learning. It is worth highlighting though that the literature on this theme is relatively nascent, with most studies focussing on the existence of sources and not necessarily estimating the impact of each individual source on productivity.

4.1.1 Identifying the micro-mechanisms and their contributions to productivity

The urban economics literature on this theme has three categories of empirical studies.

The first category of studies evaluates job search and matching effects and, to some extent, attempts to explore whether labour market operations determine the agglomeration-productivity relationship. Early empirical studies in this category provide indirect evidence on job matching as a source of urban agglomeration economies via assessing the links between larger and thicker urban labour markets and (i) greater specialisation of professional activities[38] [39], (ii) improved matching between workers and firms[40] [41], (iii) enhanced efficiency of job search[42] [43], (iv) reduced labour market churn[44] [45] and (v) reduced on-the-job training[46] [47].

For instance, using data from over 5 million workers in 454 occupations and 114 sectors extracted from the French census, Duranron and Jayet (2011) show that even after accounting for the uneven spatial distribution of industries across cities, larger cities comprise a greater proportion of workers in scarcer occupations. Similarly, Di Addario (2011) find that, for the Italian context, workers located in an area with a larger population situated within an industrial district or super district have a higher likelihood of securing employment. Bleakley and Lin (2012) find that workers exhibit lower rates of changing occupations and industries in densely populated areas, attributing this phenomenon to improved job matching facilitated by density.

[38] Garicano, L., & Hubbard, T. N. (2007). Managerial leverage is limited by the extent of the market: Hierarchies, specialization, and the utilization of lawyers' human capital. The Journal of Law and Economics, 50(1), 1-43.
[39] Duranton, G., & Jayet, H. (2011). Is the division of labour limited by the extent of the market? Evidence from French cities. Journal of Urban Economics, 69(1), 56-71.
[40] Andersson, F., Burgess, S., & Lane, J. I. (2007). Cities, matching and the productivity gains of agglomeration. Journal of Urban Economics, 61(1), 112-128.
[41] Andini, M., De Blasio, G., Duranton, G., & Strange, W. C. (2013). Marshallian labour market pooling: Evidence from Italy. Regional Science and Urban Economics, 43(6), 1008-1022.
[42] Yankow, J. J. (2009). Some empirical evidence of the efficacy of job matching in urban labor markets. *International Advances in Economic Research*, *15*, 233-244.
[43] Di Addario, S. (2011). Job search in thick markets. *Journal of Urban Economics*, *69*(3), 303-318.
[44] Wheeler, C. H. (2008). Local market scale and the pattern of job changes among young men. *Regional Science and Urban Economics*, *38*(2), 101-118.
[45] Bleakley, H., & Lin, J. (2012). Thick-market effects and churning in the labor market: Evidence from US cities. *Journal of urban economics*, *72*(2-3), 87-103.
[46] Brunello, G., & De Paola, M. (2008). Training and economic density: Some evidence form Italian provinces. *Labour Economics*, *15*(1), 118-140.
[47] Muehlemann, S., & Wolter, S. C. (2011). Firm-sponsored training and poaching externalities in regional labor markets. *Regional Science and Urban Economics*, *41*(6), 560-570.

In a first for this category, Abel and Deitz (2015)[48] provide direct evidence on job matching as a source of urban agglomeration economies. They focus on job matching amongst college graduates in the U.S. The study uses micro data from the 2010 American Community Survey along with data from the U.S. Department of Labor's Occupational Information Network (O*NET) to construct two measures of job matching consistent with the labour economics literature: (1) College Degree Match, and (2) College Major Match. The former assesses if a college graduate is employed in an occupation that necessitates a college degree, while the latter evaluates the calibre of job fit by examining if an individual's college major aligns with the job they are engaged in.

Using these measures, the study first establishes that large and dense urban environments do facilitate job matching among college graduates. The study then explores the extent to which better job matching increases individual-level wages and contributes to the urban wage premium. To do so, they compare the estimates from a standard urban wage equation with those from an extended model that includes the proposed measures of job matching. Specifically, for individual i located in metropolitan area j within a larger region k, they estimate the following urban wage regressions:

$$\ln w_i = \alpha \ln A_j + \boldsymbol{\beta X_i} + \boldsymbol{\delta M_i} + \boldsymbol{\mu Z_j} + \sigma_k + \epsilon_i$$

$$\ln w_i = \alpha' \ln A_j + \boldsymbol{\phi MATCH_i} + \boldsymbol{\beta X_i} + \boldsymbol{\delta M_i} + \boldsymbol{\mu Z_j} + \sigma_k + v_i$$

where w_i is an individual's hourly wage; A_j, $\boldsymbol{X_i}$, $\boldsymbol{M_i}$, $\boldsymbol{Z_j}$, and σ_k represent the measure of agglomeration, a vector of individual characteristics, a vector of dummy variables denoting an individual's degree major, a vector of other metropolitan area-level variables to control for differences in the characteristics of metropolitan areas, and a spatial fixed effect, respectively. $\boldsymbol{MATCH_i}$ is a vector of the proposed job matching measures; α, α', $\boldsymbol{\phi}$, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\mu}$ are parameters to be estimated, and ϵ_i and v_i represent error terms.

In the first equation, the parameter α provides a general estimate of the urban wage premium arising from all sources of urban agglomeration economies. In the second equation, since job matching is included along with the agglomeration variable, $\boldsymbol{\phi}$ represents the wage premium associated with job matching keeping other forms of agglomeration constant and α' represents the urban wage premium arising from all other sources of urban agglomeration economies excluding job matching. From these equations, Abel and Deitz (2015) infer the contribution of job matching to aggregate urban productivity by comparing α and α'. Their results suggest that better job matching among college graduates accounts for about 5 to 8% of the urban wage premium.

The second category of studies identifies the existence of the three Marshallian sources of agglomeration economies: knowledge spillovers, labour pooling, and input–output linkages. Most studies under this category compute industry-specific spatial indices of co-agglomeration, and then regress them on industry characteristics describing the three sources of agglomeration.

One of the first comprehensive studies on this theme comes from Rosenthal and Strange (2001)[49] who study the spatial concentration of manufacturing industries in the US. In their model, input sharing is proxied by the shares of manufacturing and nonmanufacturing inputs in shipments, knowledge spillovers are represented by innovations per dollar of shipment, and labour pooling is represented by the value of shipments less the value of purchased inputs divided by the number of workers, the share of management workers, and the share of workers with at least a bachelor's degree.

In a similar spirit, Ellison et al. (2010)[50] study the extent to which US manufacturing industries locate in close proximity to one another. They regress an index of co-agglomeration between the two industries on indicators of labour pooling, knowledge spillovers, and input-output linkages.

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[48] Abel, J. R., & Deitz, R. (2015). Agglomeration and job matching among college graduates. *Regional Science and Urban Economics*, *51*, 14-24.
[49] Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of urban economics*, *50*(2), 191-229.
[50] Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195-1213.

Labour pooling is represented using the correlation of occupation shares between the two industries. The share of input from the other industry and the share of output to the other industry are used as measures of input and output linkages. Technological proximity is proxied via the shares of R&D flowing to and from the other industry, and patent citations of one industry made by the other industry.

It is worth noting that the proxies for the channels of agglomeration suggested in the above studies are computed from the same quantities as the response variable, leading to structural dependence between the response and the covariates of the model. Further, Combes and Gobillon (2015) highlight that the studies underlying this category are mostly descriptive in nature and do not usually rely on a precise theoretical framework.

The third category includes case studies where distinct mechanisms of agglomeration can be evaluated by examining firms or industries, where the potential density effects are understood and can be defined. For instance, Holmes and Lee (2012)[51] analyse the factors influencing the selection of crops for individual fields, separating the influence of natural soil qualities and economies of density, that is, the benefits gained from planting neighbouring fields with the same crop.

Leveraging comprehensive geographical data on crop selection, the study develops a model to understand how farmers decide what to plant in adjacent fields under their management, such that their profits are maximised. Their findings suggest that soil attributes of neighbouring fields significantly influence planting decisions on a given field. From this relationship, they derive the structural parameters of the economies of density. Given the strong theoretical foundations underlying such approaches, Combes and Gobillon (2015) recommend exploring them further for identification of effects arising from different channels of agglomeration.

4.1.2 Implications for appraisal

In relation to the appraisal of transport investments, Eliasson and Fosgerau (2019)[52] highlight that the distinction between micro-mechanisms has important implications for the overlap between DUBs and WEIs of transport improvements. Eliasson and Fosgerau (2019) develop a spatial model to examine the effects of transport schemes concerning agglomeration mechanisms.

They identify two primary sources of WEIs resulting from transport improvements in their model: the alteration in local wage rates while keeping local employment constant, and the adjustment in local employment while maintaining local wage rates constant. They argue that the former portion of the output change is attributed to alterations in job-to-job accessibility, representing sharing and learning effects, which should be considered as WEIs. The latter portion reflects workers' decisions regarding job locations or matching effects, of which only the tax share should be regarded as WEIs.

They contend that workers aim for higher wages with improved travel times by commuting more to secure better worker-job matches. Hence, post-tax matching gains would be integrated into the valuation of travel time savings, stemming from the increased demand within the transport system following the reduction in GTCs. It is worth noting that this model explicitly critiques the basic Venables (2007) model following which agglomeration impacts for transport schemes are currently appraised within CBA.

Graham and Gibbons (2019) suggest that while the proposition presented in Eliasson and Fosgerau (2019) is reasonable, it does not seem theoretically plausible that all post tax matching benefits are valued within time savings. Eliasson and Fosgerau (2019)'s assumption that matching benefits are entirely internal to workers is inconsistent with the urban economics literature which recognises such benefits as an externality.

[51] Holmes, T. J., & Lee, S. (2012). Economies of density versus natural advantage: Crop choice on the back forty. *Review of Economics and Statistics*, *94*(1), 1-19.

[52] Eliasson, J., & Fosgerau, M. (2019). Cost-benefit analysis of transport improvements in the presence of spillovers, matching and an income tax. *Economics of Transportation*, *18*, 1-9.

Graham and Gibbons (2019) further highlight that while theoretical distinction of benefits from the different micro-mechanisms of agglomeration may be possible, their empirical separation might be challenging. This is because, ideally, to empirically disentangle the contributions, we need to identify situations where there is enough variation in the contributions with some of the forces kicking in and some not. In practice, however, all these sources are likely to act together, leading to the issue of equivalence of outcomes.

4.1.3 Conclusions and recommendations

The key points made in this section are as follows.

- Theory distinguishes the benefits of agglomeration resulting from the three key micro-mechanisms: sharing, matching, and learning, whereas, in practice, the three mechanisms are likely to act together and have the same general effect on productivity (for instance, creating gains). So, there may not be enough variation in the data to disentangle the effects, which again leads to the issue of equivalence of outcomes.
- Most previous studies in this area are, therefore, limited to identifying the existence of the sources of agglomeration, rather than linking these sources to productivity.
- To isolate the contributions from various sources of agglomeration, one may consider exploring natural experiments where there is enough variation in the contributions with one of the forces are in play and others are not. However, it is worth emphasising that it is hard to identify such situations in practice.

The section concludes with the following recommendation for future work.

R4 Contributions from distinct micro-mechanisms of agglomeration (sharing, matching, and learning) should be estimated via models that exploit natural experiments where enough variation in the contributions can be guaranteed with some of the micro-mechanisms kicking in and some not. Consideration should be given as to whether the resulting evidence is suitable for use in appraisal.

4.2 ‘Real’ and ‘effective’ density benefits and impedance measures

R5 Recommendation: Estimation of real density-driven benefits of agglomeration should be conducted by exploring novel measures of impedance for ATEM variables, including potential measures that combine observed travel flows (trips) and GTCs.

Given that there is no absolute measure of agglomeration, ‘access to economic mass (ATEM)’ is often used as a proxy to represent it.

4.2.1 Access to economic mass and ‘effective’ density

The measure of ATEM used in TAG is referred to as ‘effective density (ED)’, which seeks to measure the impact of changes in generalised travel costs and employment location on the strength of an agglomeration. The ED measure (ρ_i) for zone $i, i = 1, \dots, n$ is calculated as:

$$\rho_i = \sum_{j=1}^{n} m_j \cdot f(\bar{g}_{ij})$$

where m_j is a measure of economic scale or mass at zone j. $f\,(.)$ represents the impedance function, which is a decreasing function of the cost ($\bar{g}_{ij}$) of travelling from origin i to destination j. As demonstrated by Graham and Gibbons (2019), the ED measure is designed to (i) capture the effect of both scale and proximity of economic mass in space, (ii) allow measurement of agglomeration via a flexible spatial framework that is, at large, independent of arbitrary boundaries, and (iii) involve a representation of transport accessibility via the impedance function. ED essentially describes the market potential of a given zone and represents a kind of aggregated density effect and is, therefore, referred to as effective density.

Candidate measures of economic mass include GVA, employment and population, although the latter two are more commonly used due to the availability of more granular data on these measures. Graham and Gibbons (2019) demonstrate that both employment-based and population-based measures of mass produce ED values of similar spatial patterns, given they can represent economic scale well. It is, of course, possible to have the sum of population and employment as the measure of economic mass.

The impedance function represents the resistance in access to economic mass. Potential measures of impedance include distance (could be Euclidean or network-based/ route-specific), travel time, average speed, the monetary cost of travel, or the generalised travel cost, GTC (say, time, price, and monetary evaluation of trip quality).

In transport modelling, the most widely used impedance measure is GTC, which can be calculated for different modes. For the same trip, this measure can vary by time of day depending upon travel conditions. GTC based impedance measure is appealing for empirical work because they consider network congestion and therefore more accurately represent the true difficulty in accessing economic mass.

However, as seen in Section 3.1, without a change in the fundamental approach used to calculate WEIs of agglomeration, GTC based elasticities cannot be validly used in empirical calculations of externalities of agglomeration. This is because econometric estimation of GTC elasticities cannot separate productivity gains induced via the WEIs of agglomeration from DUBs induced via time savings.

To reduce potential for overlap, the current approximation in TAG utilises a Euclidean distance-derived ED within the econometric model of agglomeration. Graham and Gibbons (2019) show that for TfL data, the correlation between the GTC-based ED and Euclidean distance-based ED is 0.927.

4.2.2 'Effective' versus 'real' density and implications for appraisal

It is worth emphasising that a pure GTC-based ATEM measure is limited in its ability to capture the 'real' density-driven benefits of agglomeration. We explain this limitation via an example. Transport improvements increase capacity, which is highly likely to result in higher traffic volumes, but in a way that does not affect generalized travel costs (GTCs).

This will imply that the amount of activity or the intensity of interactions in the economy has increased, thereby enlarging the market. However, the current ED-based calculations will suggest no impact on productivity, which cannot be true.

Therefore, potential extensions to ATEM need to be explored such that the 'real' density-driven benefits of transport improvements are appropriately captured. One way to capture real density effects is to use actual travel flows (that is, observed number of trips) in calculations. Relevant OD matrices for calculations can be generated using data sources such as origin-destination (flow) records produced from census, mobile network data, and Meta (Facebook) data-for-good, among others.

Nevertheless, it is important to note that a certain segment of agglomeration mechanisms, particularly those related to matching, may not stem from direct interactions. The efficiency of matching is related to the pool of available firms and workers and it may well be the case that each worker does not necessarily interact with all possible firms they could choose from.

However, choice of a bigger pool of opportunities is likely to improve the efficiency of matching. As a result, increase in market opportunities in response to a transport improvement may not necessarily materialise in terms of flows. This report, therefore, recommends exploring candidate impedance measures that are derived from a combination of observed flows and GTCs/ Euclidean distances.

Observed flows (f_{ij}) can be incorporated as follows:

$$\rho_i' = \sum_{j=1}^{n} f_{ij} \cdot m_j \cdot f(\bar{g}_{ij}),$$

with

$$\frac{\partial \log \rho_i'}{\partial \log f_{i1}} = \frac{f_{i1} \cdot m_1 \cdot f(\bar{g}_{i1})}{\rho_i'}$$

4.2.3 Conclusions and recommendations

The key points made in this section are as follows.

- As there is no definitive metric for agglomeration, access to economic mass (ATEM) serves as a proxy to depict it. TAG recommends the use of effective density (ED) as a measure of ATEM, which characterises the market potential of a particular area. The ED proxy combines a representation of the spatial distribution of economic mass and an impedance function signifying the difficulty in accessing the economic mass.
- Potential measures of economic mass commonly include GVA, employment and population, but can also include a combination of these.
- The current TAG calculation of agglomeration externalities employs a Euclidean distance-based measure to represent impedance in the ATEM. The intuition is to remove variance in travel costs when estimating the agglomeration elasticity, thereby reducing potential for direct capture of travel time productivity effects in the elasticity.
- Yet, the use of GTC-based impedance is more appealing to practitioners for two key reasons: (a) Adopting GTC-based ATEM makes outputs from transport models consistent with inputs to the econometric model of agglomeration, and (b) GTC-based ATEM can be calculated for different modes and can vary by time of the day, thereby taking into account network conditions and therefore more accurately representing the impedance in access to economic mass.
- While by changing in the fundamental approach to calculate agglomeration externalities, GTC-based ATEM can validly be used in appraisal, it is worth noting that the measure is limited in its ability to capture the ‘real’ density-driven benefits of agglomeration. For instance, there may be scenarios where transport improvements may generate changes in traffic volumes without affecting the GTCs. Under such scenarios, the GTC-based ATEM will fail to capture the increase in market size and, consequently, the associated productivity gains.
- A potential solution to capture the real density-driven benefits of transport improvements is to use actual travel flows (that is, observed number of trips) in calculations. Potential ATEM measures that combine observed flows and Euclidean distances are worthy of future investigation.

The section concludes with the following recommendation for future work.

R5 Estimation of real density-driven benefits of agglomeration should be conducted by exploring novel measures of impedance for ATEM variables, including potential measures that combine observed travel flows (trips) and GTCs.

4.3 The functional form of decay parameters

R6	**Recommendation: Estimation of the spatial scope (decay) of agglomeration economies should be done by implementing and comparing alternative approaches to model decay, including modelling the decay function flexibly via semi-parametric regression. Judgement should be made to identify the form that is both analytically tractable and best approximates the observed pattern of decay.**

As described previously, agglomeration economies occur when agents derive benefits from being in close proximity to one another. However, the geographic scope over which agents could be described as proximate such that they generate these external benefits remains unclear. There is evidence in the literature that suggests that agglomeration effects tend to decrease in magnitude beyond 5 to 10 km from source[53] [54] [55]. Another study highlights that the agglomeration impact on productivity declines steeply with traveling time and becomes insignificant beyond approximately 80 minutes[56]. In a similar vein, Rosenthal and Strange (2003)[57] find that the gains from agglomeration economies arising from spatial concentration diminish rapidly over traveling distances for most industries in the US, before decreasing more slowly. Duranton and Overman (2005)[58] find positive effects from collocation within 50 kilometres. Interestingly, another recent study[59] finds these spatial patterns to be even more complex, with agglomeration on short distances (<5 km) insignificantly affecting wages in the Netherlands. Further, they find significant and positive effect on medium distances (5–10 km), which ultimately becomes insignificant after 40–80 km.

4.3.1 Common approaches to model the spatial scope of agglomeration economies

To take such insights into account, construction of the agglomeration term ρ_i for empirical work should represent the potential opportunities for a firm to benefit from the agglomeration mechanisms in their locality while also clearly defining the meaning of 'locality'. In a standard set-up, ρ_i is defined as economic mass in the geographical neighbourhood of each agent i. Locality is then defined via ease of access to this economic mass by aggregating economic mass with higher weights applied to locations close to agent i, and lower weights to those further away. The agglomeration index, thus, has the following general structure:

$$\rho_i = \sum_{j=1}^{n} m_j \cdot f(c_{ij})$$

where the weights $f(c_{ij})$ are decreasing in the costs c_{ij} incurred in moving between location i and locations j, and $m_j$is the measure of economic mass (say, employment or population) used to create the agglomeration index. There are several ways of specifying the weights $f(c_{ij})$. These include weighing for 'cumulative opportunities', where $f\left(c_{ij}\right) = 1$ if j is within a given distance from i, zero otherwise; exponential weights $f\left(c_{ij}\right) = e^{-\alpha c_{ij}}$; logistic weights $f\left(c_{ij}\right) = [1 + e^{-\alpha c_{ij}}]^{-1}$ or inverse cost weights $f\left(c_{ij}\right) = c_{ij}^{-\alpha}$.

[53] Rosenthal, S. S., & Strange, W. C. (2008). The attenuation of human capital spillovers. *Journal of Urban Economics*, *64*(2), 373-389.
[54] Melo, P. C., Graham, D. J., & Noland, R. B. (2009). A meta-analysis of estimates of urban agglomeration economies. *Regional science and urban Economics*, *39*(3), 332-342.
[55] de Almeida, E. T., Neto, R. D. M. S., & Rocha, R. D. M. (2023). The spatial scope of agglomeration economies in Brazil. *Journal of Regional Science*, *63*(4), 820-863.
[56] Rice, P., Venables, A. J., & Patacchini, E. (2006). Spatial determinants of productivity: Analysis for the regions of Great Britain. Regional science and urban economics, 36(6), 727-752.
[57] Rosenthal, S. S., & Strange, W. C. (2003). Geography, industrial organization, and agglomeration. *review of Economics and Statistics*, *85*(2), 377-393.
[58] Duranton, G., & Overman, H. G. (2005). Testing for localization using micro-geographic data. *The Review of Economic Studies*, *72*(4), 1077-1106.
[59] Verstraten, P., Verweij, G., & Zwaneveld, P. J. (2019). Complexities in the spatial scope of agglomeration economies. *Journal of Regional Science*, *59*(1), 29-55.

Currently, TAG adopts an inverse cost weighting specification where the ED index includes an exponent α on the chosen measure of impedance (Euclidean distance), which is commonly known as the distance decay parameter. Graham and Gibbons (2019) show that this parameter has three important implications for transport appraisal.

First, it primarily determines the sensitivity of agglomeration index (ED) to changes in impedance. The higher the value, the higher is the sensitivity of the ED index of agglomeration to reductions in the impedance of travel. Second, advancements in transportation networks will notably impact the overall density of an area if they improve connections to locations already vital to its density. Reductions in travel barriers to distant, less significant areas will not produce substantial effects. Third, the ED index alone does not dictate whether it's more advantageous to prioritise enhancing densely populated or sparsely populated regions.

However, other factors like the quantity of firms or workers benefiting from productivity enhancements due to agglomeration, or the initial average productivity of the area, could influence the results of the cost-benefit assessment.

In practical applications, when spatial units of analysis are relatively small, the value of α is often assumed to be 1. However, explicit estimation of α can also be done for transport appraisal. For instance, using non-linear least squares estimation, Graham et al. (2010)[60] obtained sector-specific point estimates for the distance decay parameter ranging from 1.06 to 1.48. Their results suggest that the productivity effects of agglomeration diminish more rapidly over traveling distances to surrounding economic activities for service firms than for manufacturing firms.

It is worth noting that use of the exponent α is one way to represent the importance of proximity and the decay of agglomeration with distance. Its advantage lies in the fact that it necessitates the estimation and insertion of only one parameter into appraisal calculations.

Nevertheless, there exists other approaches too. For instance, in the recent quantitative spatial models, the spatial decay of production externalities with travel time has been calibrated via adopting an iceberg transport cost model that essentially uses an exponential weighting (see, for instance, Redding and Rossi-Hansberg (2017)[61] and Ahlfeldt et al. (2015)[62]). It is worth noting though that the assumptions of an iceberg transport cost model stand in contrast with evidence of economies of scale and distance in transport.

4.3.2 Flexible modelling of the spatial decay of agglomeration economies

An alternative and more flexible approach comprises representing agglomeration through economic mass at several discrete distance (or time) bands, commonly known as the piecemeal distance (or time) band method. Graham et al. (2010) uses this approach to study the decay of agglomeration effects with distance. They aggregate employment measures at various distance bands for each firm in the sample individually. For instance, employment at size band θ with lower radius $r_{0\theta}$ and upper radius $r_{1\theta}$ is defined as

$$m_{\theta it} = \sum_{j \in \{r_{0\theta i}, r_{1\theta i}\}} m_{jt}$$

where $\{r_{0\theta i}, r_{1\theta i}\}$ is the set of all firms located within the boundaries of size band θ at time t. Graham et al. (2010) use distance bands with boundaries at 2.5, 5, 10, 25, 50 and 75 km. The complete set size band employments can then be used as the measure of ρ_{it},

60 Graham, D. J., Gibbons, S., & Martin, R. (2010). The spatial decay of agglomeration economies: estimates for use in transport appraisal. DfT: London.

61 Redding, S. J., & Rossi-Hansberg, E. (2017). Quantitative spatial economics. Annual Review of Economics, 9, 21-58.

62 Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica*, *83*(6), 2127-2189.

$$\rho_{it} = \sum_{\theta} \delta_\theta \ln m_{\theta it}.$$

The parameter δ_θ is then used to study the decay of agglomeration spillovers.

An even more general approach comprises estimating the decay function $f(c_{ijt})$ via semi-parametric regression, that is, via using smoothing splines or kernel (local) regression. It involves averaging spatially distributed economic mass to create a smooth spatial surface. It is fully data-driven approach where the objective is to find the functional form of $f(.)$ to best fit the data from which it is generated. An example application can be found in Coombes and Raybould (2001)[63].

4.3.3 Conclusions and recommendations

The key points made in this section are as follows.

- Agglomeration indices constructed for empirical analysis should reflect the potential benefits that an economic agent can gain from agglomeration mechanisms in its locality, while also distinctly defining the concept of 'locality'.
- Accordingly, the level of agglomeration experienced by a given agent is generally defined by aggregating economic mass in the geographical neighbourhood of the agent with higher weights applied to locations close to the agent, and lower weights to those further away.
- To represent the importance of proximity and the spatial scope of agglomeration, TAG currently uses an exponent on the chosen measure of impedance (Euclidean distance) within the ED index. This exponent is commonly known as the distance decay parameter. The advantage of this approach lies in the fact that it necessitates the estimation and insertion of only one parameter into appraisal calculations.
- More flexible approaches to represent this phenomenon include the piecemeal distance (or cost) band method or modelling of distance (or cost) decay via semi-parametric regression.

The section concludes with the following recommendation for future work.

R6 Estimation of the spatial scope (decay) of agglomeration economies should be done by implementing and comparing alternative approaches to model decay, including modelling the decay function flexibly via semi-parametric regression. Judgement should be made to identify the form that is both analytically tractable and best approximates the observed pattern of decay.

4.4 The level of spatial aggregation

R7 Recommendation: Sensitivity of agglomeration elasticities to zonal definitions should be tested by estimating the agglomeration model with data aggregated at different spatial levels. Results should be compared to identify which evidence is more robust and suitable for utilisation in appraisal.

As seen before, empirical estimation of agglomeration elasticities entails aggregation of scattered geocoded data on economic agents into discrete spatial units, referred to as zones. In most practical applications, the adopted zoning system is consistent with pre-defined administrative boundaries.

For instance, the agglomeration elasticity calculations performed in Graham (2007) uses British wards as the spatial unit of aggregation. Some studies have also divided the entire geographical area of analysis into 1 kilometre x 1 kilometre cells, which are considered as the spatial unit of

[63] Coombes, M., & Raybould, S. (2001). Public policy and population distribution: Developing appropriate indicators of settlement patterns. *Environment and Planning C: Government and Policy*, *19*(2), 223-248.

analysis[64] [65]. In other areas of spatial data analysis, the use of H3 Spatial index[66] developed by Uber to measure spatial differences in accessibility has also been popular recently, owing to their computational efficiency.

4.4.1 The modifiable arial unit problem

While Graham and Gibbons (2019) emphasise that the ED measure used in TAG calculations are designed to be free of arbitrary spatial boundaries, Briant et al. (2010)[67] indicate that the chosen unit of aggregation has important implications for statistical inference. The sensitivity of statistical estimates to the choice of a particular spatial level of aggregation is commonly referred to as the Modifiable Areal Unit Problem (MAUP). Using data from France, Briant et al. (2010) further demonstrate that differences in size of the spatial unit does have a pronounced effect on the estimated agglomeration elasticity, especially when moving from a zoning system that involves very small spatial units to a one involving very large units.

However, it is worth noting that these differences only apply when agglomeration is measured via local density (economic mass per unit area). Upon inclusion of a market potential measure similar to the ED measure in TAG, the agglomeration elasticities are shown to not vary substantially with size of the zoning system. Most importantly, Briant et al. (2010) find that the MAUP concerns are more severe when no adjustments are made for potential sources of confounding in estimation of the agglomeration model.

4.4.2 The sensitivity of agglomeration elasticities to zonal definitions

Another recent study by Cottineau et al. (2018)[68] revisits the question of spatial aggregation and argues that choice of zoning system is important, specifically, because across different zonal definitions, there may be different mechanisms of agglomeration that are dominant. They point out that the three micro-foundations of agglomeration: sharing, matching, and learning involve different set of economic agents and interactions.

In the context of matching, both firms and workers from the entire labour market engage in the process, with more participants increasing the likelihood of efficient matches between supply and demand. Regarding learning, firms and workers are expected to benefit from knowledge spillovers, primarily occurring between closely situated production areas specialised in related industries, where knowledge is accumulated and disseminated through face-to-face interactions. In terms of sharing, the extent and type of mechanism depend on what is shared. For indivisible facilities, these can range from very localised amenities like shared office spaces and fast broadband, to neighbourhood amenities such as underground stations and parks, and regional facilities like airports and patent registration offices.

Conversely, sharing of risk, various inputs, and narrow industrial specialisation suggests involvement of entire urban and regional economies. According to them, these diverse networks of agents imply differing policy implications, and policies must adjust their targets and geographical scales based on the mechanism at play. They further highlight that empirical evidence from Rosenthal and Strange (2001)[69] and Mori and Smith (2015)[70], indicating that localisation

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[64] de Almeida, E. T., Neto, R. D. M. S., & Rocha, R. D. M. (2023). The spatial scope of agglomeration economies in Brazil. *Journal of Regional Science*, *63*(4), 820-863.

[65] Andersson, M., Larsson, J. P., & Wernberg, J. (2019). The economic microgeography of diversity and specialization externalities–firm-level evidence from Swedish cities. *Research Policy*, *48*(6), 1385-1398.

[66] https://www.uber.com/en-GB/blog/h3/

[67] Briant, A., Combes, P. P., & Lafourcade, M. (2010). Dots to boxes: Do the size and shape of spatial units jeopardize economic geography estimations?. *Journal of Urban Economics*, *67*(3), 287-302.

[68] Cottineau, C., Finance, O., Hatna, E., Arcaute, E., & Batty, M. (2019). Defining urban clusters to detect agglomeration economies. *Environment and Planning B: Urban Analytics and City Science*, *46*(9), 1611-1626.

[69] Rosenthal, S. S., & Strange, W. C. (2001). The determinants of agglomeration. *Journal of urban economics*, *50*(2), 191-229.

[70] Mori, T., & Smith, T. E. (2015). On the spatial scale of industrial agglomerations. *Journal of Urban Economics*, *89*, 1-20.

economies vary with geographical scale and across industries, suggests that there is no single ideal definition of zoning system and empirical work must adapt to theoretical questions rather than being dictated by the availability of data. In other words, the ideal choice of the zoning system is likely to be context dependent, for instance, small units for local transport schemes and larger units for national ones.

Using micro-data from France, Cottineau et al. (2018) further find that size of zoning system does have a significant impact on the estimated agglomeration elasticity. In particular, they find that a local partitioning (commues-based) of the French data yields higher agglomeration elasticities than a regional (NUTS-3 based) one, when using employment density as the measure of agglomeration. It is worth noting that similar to Briant et al. (2010), their analysis uses a local measure of density. Moreover, their conclusions are based on inferring associations between density and productivity, rather than establishing causality. Relatedly, Laird and Aalen (2022)[71] recommended calculating agglomeration benefits at the lowest possible level of aggregation to minimise MAUP concerns, however, even their conclusions stem from estimation of the agglomeration model without appropriate corrections for endogeneity.

More recently, some studies[72] [73] [74] have explored data-driven ways of delineating the zonal system for analyses of economic performance. More specifically, the studies highlighted here have partitioned large geographical areas into homogeneous economic clusters via the use of density and flow-based hierarchical clustering algorithms. In their study, Cottineau et al. (2018) adopt a similar algorithm to identify homogeneous economic regions in France, which they further use to understand whether larger cities are richer. It may be worth exploring such approaches to test the sensitivity of agglomeration estimates to zonal definitions.

4.4.3 Practical considerations for changes in zoning for TAG

Noting the sensitivities of agglomeration elasticities to zonal definitions mentioned above, it is advisable that any future updates to agglomeration elasticities in TAG are estimated at a level that is sensible for the UK but also that is practical in terms of carrying out the assessment of transport projects for appraisal purposes. This means choosing a zonal level that is functional for practitioners to calculate agglomeration benefits as well as for DfT to provide the necessary data that is required for the analysis, in an updated version of the current Wider Impacts dataset[75] that DfT provide, which currently includes data by Local Authority.

In this context, a potential option would be to carry out this analysis at MSOA level. This would have the following advantages and disadvantages:

- Significant data is available at MSOA level including employment data from the Census or the Business Register and Employment Survey, which would facilitate the task of updating the employment projections in total and by sector provided in the Wider Impacts dataset
- However, productivity data is not publicly available at MSOA level, which would require either making assumptions that productivity does not vary at Local Authority level or engaging with the ONS in producing something more granular for instance through the business data that the ONS gathers.
- A further advantage of choosing MSOAs is that a lot of transport models typically build their zoning taking MSOAs as a starting point thus facilitating the conversion of Generalised

[71] Tveter, E., Laird, J. J., & Aalen, P. (2022). Spatial aggregation error and agglomeration benefits from transport improvements. *Transportation Research Part A: Policy and Practice*, *164*, 257-269.

[72] Cao, W., Dong, L., Cheng, Y., Wu, L., Guo, Q., & Liu, Y. (2023). Constructing multi-level urban clusters based on population distributions and interactions. *Computers, Environment and Urban Systems*, *99*, 101897.

[73] Cottineau, C., & Vanhoof, M. (2019). Mobile phone indicators and their relation to the socioeconomic organisation of cities. *ISPRS International Journal of Geo-Information*, *8*(1), 19.

[74] Raimbault, J. (2019). Multi-dimensional urban network percolation. *Journal of Interdisciplinary Methodologies and Issues in Sciences*, *5*.

[75] The current Wider Impacts Dataset is available at https://www.gov.uk/government/publications/tag-economic-impacts-worksheets.

Costs to the correct zoning system required to calculate agglomeration benefits. Note that models typically have much larger zones outside of the area of interest, therefore there might be a case to still use Local Authorities outside of the key study area as it will not be possible to convert GCs to and from large zones into a more disaggregated zoning system by MSOA.

4.4.4 Conclusions and recommendations

The key points made in this section are as follows.

- For empirical estimation of the agglomeration model, micro data on economic agents are aggregated into discrete spatial units, commonly referred to as zones. In most practical applications, the zoning system adopted for calculations is consistent with pre-defined administrative boundaries.
- Nonetheless, a series of studies have shown that the chosen unit of aggregation has important implications for statistical inference. This issue is commonly recognised in the literature as the Modifiable Areal Unit Problem (MAUP).
- The literature suggests that calculating agglomeration benefits at the lowest possible level of aggregation to minimise MAUP concerns. Nevertheless, the ideal choice of the zoning system is likely to be context dependent, say, small units for local transport schemes and larger units for national ones.

The section concludes with the following recommendation for future work.

R7 Sensitivity of agglomeration elasticities to zonal definitions should be tested by estimating the agglomeration model with data aggregated at different spatial levels. Results should be compared to identify which evidence is more robust and suitable for utilisation in appraisal.

4.5 Endogeneity issues, econometric estimation, and validation methods

R8 Recommendation: Adjustments for observed and unobserved confounding and reverse causality should be made within the econometric model of agglomeration to obtain agglomeration elasticities that are robust and suitable for use in appraisal.

As described in Section 3.1, a key quantity of interest in the calculation of the WEIs of agglomeration is the impact (say, productivity gains) generated by a change in agglomeration. In this section, we introduce the key features and challenges associated with the empirical estimation of this impact.

We have n units of observation in our sample, indexed by $i, i = (1, \dots, n)$. We want to infer what would happen to a defined outcome Y (for instance, productivity) when a transport improvement brings about a change in the level of agglomeration, D, the 'treatment'. The treatment in question is continuous, that is, $D \subseteq \mathbb{R}$.

The key quantity of interest in our calculations is the average treatment effect,

$$\tau(\rho) = \mathbb{E}[Y_i(\rho) - Y_i(\rho_0)]$$

which signifies the difference between expected outcomes for all units under treatment level $D_i = \rho$, relative to some reference level of treatment $D_i = \rho_0$, equivalently, the difference between the average potential outcomes under treatment levels $D_i = \rho$ and $D_i = \rho_0$.

Based on the above equation, the causal estimate of the impact of the treatment can be obtained by comparing the average outcome in treated units and the average counterfactual outcome in those units if untreated or treated at some less intense level. The fundamental challenge herein is that the counterfactual outcomes for treated units remain unobserved.

Nevertheless, the potential outcomes approach suggests that causal effects can still be identified if the focus remains on estimating average causal effects over the population. More specifically, the missing counterfactual outcome, (or the missing average potential outcomes) can be reconstructed via average outcomes using appropriate econometric tools. This corresponds to estimating the difference between the average outcomes of units in more connected places to those in less connected places, netting out any difference between these two groups of units that would lead differences in outcomes even without any difference in their connectivity.

4.5.1 Sources of endogeneity

Extraneous factors that simultaneously determine both agglomeration and productivity can obscure their actual causal relationship in the observed economic data. Graham and Gibbons (2019) suggest that such factors, commonly referred as sources of endogeneity, emerge through six key processes:

a) Endogeneity may occur due to the presence of unobserved firm-level sources of productivity that are not only crucial to the firm's choice of inputs, and thereby its TFP[76], but may be determined by local technology factors such as agglomeration. Moreover, these effects also occur in factor price (wage) models as they are transmitted to factor demand equations via optimising behaviour.

b) Endogeneity may also occur due to the absence of knowledge on a firm's market exit decisions[77], which may be determined by agglomeration. In particular, firms located in clusters of higher agglomeration may experience more competition, which could result in the exit of less productive firms from the market. This threat is specifically crucial in the context of balanced panel datasets that inherently contain only surviving firms and can therefore bias the estimation of TFP.

c) Endogeneity biases may emerge via unobserved heterogeneity in output prices of firms, which have a systematic correlation with market competition, and thereby with agglomeration. Such biases effect both TFP and wage models as their expressions depend on output prices.

d) As described in Section 3.1, endogeneity may appear due to spatial sorting or self-selection of firms, which occurs when firms within the same industry derive unobserved productivity benefits by engaging in different activities across different locations. This phenomenon can be more commonly when high quality workers self-select zones with high-quality jobs. Such unobserved heterogeneity is often correlated with the level of agglomeration.

e) The relationship between agglomeration and productivity may be simultaneously determined. As shown by Graham (2010)[78], higher productivity locations may attract more private investment over time leading to larger agglomeration and a consequent increase in productivity. This threat occurs in both TFP and wage models. Failure to account for this reverse causality between productivity and agglomeration may produce biased and inconsistent estimates of agglomeration economies.

f) Additional confounding may emerge from unobserved components of local technology, such as specific characteristics of local input and output markets, that may be determine both agglomeration and productivity.

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[76] Van Beveren, I. (2012). Total factor productivity estimation: A practical review. *Journal of economic surveys*, *26*(1), 98-128.

[77] Ackerberg, D., Benkard, C. L., Berry, S., & Pakes, A. (2007). Econometric tools for analyzing market outcomes. *Handbook of econometrics*, *6*, 4171-4276.

[78] Graham, D. J., Melo, P. S., Jiwattanakulpaisarn, P., & Noland, R. B. (2010). Testing for causality between productivity and agglomeration economies. *Journal of regional Science*, *50*(5), 935-951.

4.5.2 Adjusting for potential biases due to endogeneity

Two broad categories of approaches are routinely employed in the literature with the attempt to address the above sources of endogeneity, both being based on the use of micro-level panel data:

a) Use of panel individual effects, within or first-differenced estimation

b) Estimation based on panel instrumental variables (IV) or panel control function (CF)

Below, these methods are discussed in the context of the agglomeration model which can take the following additive form:

$$y_{ict} \;=\; f(\rho_{ct}) + \eta_{ct} + u_{it} + e_{ict}$$

where y_{ict} represents the productivity of firm or worker i in region c and time t, ρ_{ct} represents the strength of agglomeration (via the ATEM measure) in region c and time t. η_{ct} and u_{it} represent unobserved area and firm/ worker effects, respectively, both of which are correlated with ρ_{ct}, and $e_{ict}$is the random error term.

The first set of methods highlighted above anticipate the unobserved area and firm/ worker effects to be fixed over time, $\eta_{ct} = \eta_c$ and $u_{it} = u_i$, and adjust for these effects via (a) inclusion of fixed area-specific and firm/ worker-specific dummies, or (b) differencing the data withing area, firm/ worker units over time (within-transformation), or (c) differencing the data between time periods (first-differencing).

Consistency of these methods depend on the absence of time-variant confounding, which is potentially unrealistic in most empirical settings. Moreover, as Graham and Gibbons (2019) note, such methods are less practical for short panels where temporal variation in ρ_{ct} is lacking. In particular, when ρ is measured using economic mass and Euclidean distance, temporal variation in ρ in a balanced panel of firms can only occur due to variation in economic mass, which are often too small for practical use.

Nevertheless, such methods may be useful in wage models as workers are more likely to move across areas in subsequent time periods, for instance, due to job changes. In this case, the wage equation is

$$w_{ict} \;=\; f(\rho_{ct}) + \eta_c + e_{ict},$$

within-individual transformation of which eliminates the time-invariant worker and area effects. The function of interest f(.) can then be estimated from the variance in effective density for individual workers resulting from their movement from one area c to another.

The second set of methods highlighted above allow adjustments for OVB resulting from both time invariant and time-varying confounding and other potential sources of endogeneity such as reverse causality.

In Panel IV models, time invariant confounding can be addressed via inclusion of unit-level fixed effects, and the other spurious influences (time-varying confounding and reverse-causality) can be nullified via the use of appropriate IVs. There are two criteria for the IVs to be valid: (i) the relevance criterion which requires that the selected IVs must be highly correlated with the agglomeration covariate, and (ii) the exogeneity criterion which states that the selected IVs must not directly determine the response (say, productivity).

The most commonly adopted identification strategy proposed in the literature is to use long-lagged values of population or employment density, or historic transport networks plans, to instrument for present values of agglomeration (see, for instance, Rice et al. (2006)).

Other popular external instruments include land area and geological data such as soil characteristics, an example application of which can be found in Rosenthal and Strange (2008). In their working study, Anupriya et al. (2023)[79] determine a novel instrument for agglomeration that is derived from traffic casualty data. In particular, they use the severity of traffic casualties among active mode users and motorcyclists during peak hours as a relevant and exogenous instrument for agglomeration.

The relevance of selected instruments can be tested using the Stock and Yogo weak instrument F-test[80]. Further, the exogeneity criterion is most commonly tested in the literature using the Sargan–Hansen J test[81] of over-identifying restrictions. However, these diagnostic statistics do not provide a full-proof means for detecting an inadequate instrument specification (see, for instance, Kriviet and Kripfganz (2021)[82]).

In the absence of valid external instruments, suitable IVs can also be derived from the panel nature of datasets routinely used in calculations. In particular, lagged differences of the agglomeration measure are used as IVs for equations in levels and lag levels as IVs for differenced equations. Estimation proceeds via defining and solving a set of moment conditions within the generalised method of moments (GMM) framework.

In Panel CF approaches, proxies for unobserved productivity are introduced into the production function as an additional model component for consistent estimation of the model parameters. These proxies might include lagged inputs of the production process. The CF approach can avoid the challenge of identifying valid instruments, provided that the researcher is prepared to adopt strong theoretical premises. Typically, CF techniques necessitate the inclusion of exogenous variables that influence the endogenous variable without directly affecting the outcome (see Graham and Gibbons (2019) for a detailed discussion on CF approaches).

4.5.3 Conclusions and recommendations

The key points made in this section are as follows.

- Confounding factors such as unobserved firm-level sources of productivity that concurrently impact both agglomeration and productivity and other sources endogeneity such as reverse causality can obstruct the determination of a causal linkage within the analysed economic data.
- It is, therefore, important to adjust for potential biases from endogeneity in estimation of the econometric model of agglomeration.
- Consistency of panel individual effects, within or first-differenced estimation commonly employed in calculations requires the absence of time-variant confounding, which is potentially unrealistic in most empirical settings.
- Panel IV and Panel CF approaches provide a more well-rounded means to address biases from time-invariant and time-varying confounding and other sources of endogeneity such as reverse causality. The former approach requires valid IVs (strong correlated with agglomeration but purely exogenous to productivity) for identification, while the latter approach requires theoretical assumptions on firm behaviour to hold.

The section concludes with the following recommendation for future work.

R8 Adjustments for observed and unobserved confounding and reverse causality should be made within the econometric model of agglomeration to obtain agglomeration elasticities that are robust and suitable for use in appraisal.

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[79] Anupriya, Graham, D.J., & Bansal, P. (2023). Testing for non-linearity of agglomeration effects. Working paper: Imperial College London.
[80] Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear IV regression.
[81] Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the econometric society*, 393-415.
[82] Kiviet, J. F., & Kripfganz, S. (2021). Instrument approval by the Sargan test and its consequences for coefficient estimation. *Economics Letters*, *205*, 109935.

4.6 Non-linearities in functional forms

R9	**Recommendation: The econometric model of agglomeration should be designed to capture potential non-linearities of agglomeration effects, which can be achieved by flexibly modelling the agglomeration-productivity relationship using non-parametric or semi-parametric regression. Implications of the results for appraisal should be evaluated.**

Economic theory suggests that the organisation of the spatial economy is determined by two broad categories of competing forces: centripetal and centrifugal forces[83]. Centripetal forces are mainly those of agglomeration, which lead to the concentration of economic activity; centrifugal forces refer to the corresponding 'disbenefits' of concentration arising from higher factor prices (say, land and rents), congestion and other costs.

It is due to the co-existence of these opposing forces that we do not find economic activity to be organised either as a single large concentration, or distributed randomly, rather we see several geographically separated and differently sized concentrations.

4.6.1 Do agglomeration economies scale non-linearly with city size?

An important question that arises is: What implication does the observed spatial organisation of economic activity have for agglomeration economies? Do areas of varying concentration exhibit varying levels of agglomeration effects? Interestingly, a meta-analysis of the literature on urban agglomeration economies conducted by Melo et al. (2009)[84] finds large differences in the size of elasticity estimates across countries. This may be taken as indirect evidence on the existence of heterogeneous productivity effects across ranges of agglomeration.

It is worth noting that most existing studies estimate a log-linear relationship between agglomeration and productivity, which corresponds to a concave and non-decreasing function in levels. However, as Combes and Gobillon (2015) point out, the assumed functional form is just an approximation, which is rather inconsistent with economic theory that predicts the marginal returns to agglomeration to decrease with city size, for instance, due to higher costs of congestion, as the city grows. They also highlight that such decreases may also apply to the sources of agglomeration.

For instance, large human capital externalities may be generated from the first skilled workers in a location, however, the marginal gain from one additional skilled worker is lower when the existing number of skilled workers is already high. Combes and Gobillon (2015) further predict the agglomeration-productivity relationship to be concave and bell-shaped curve, resulting from the interplay between the costs (say, congestion and rent) and benefits (productivity effects) of agglomeration.

4.6.2 Empirical evidence on the presence of non-linearities

Does city scale really have heterogeneous effects across ranges of agglomeration, with positive and negative gradients, thresholds, and flat regions across the range? If such heterogeneity exists, does it feature more for some industries than for others? In a first, using data from the UK, Graham and Dender (2011)[85] demonstrate the presence of significant non-linearities in agglomeration-productivity relationship aggregated across all industries. The estimated relationship is approximately concave and bell-shaped as predicted by Combes and Gobillon (2015).

Interestingly, Graham and Dender (2011) find no positive effect of agglomeration over broad ranges of the data. They adopt a one-step procedure, where the agglomeration covariate is specified within the production function and the agglomeration-productivity relationship is obtained

[83] Fujita, M., & Thisse, J. F. (2002). Agglomeration and market interaction. *Available at SSRN 315966*.

[84] Melo, P. C., Graham, D. J., & Noland, R. B. (2009). A meta-analysis of estimates of urban agglomeration economies. *Regional science and urban Economics*, *39*(3), 332-342.

[85] Graham, D. J., & Dender, K. V. (2011). Estimating the agglomeration benefits of transport investments: some tests for stability. *Transportation*, *38*, 409-426.

via fitting a semiparametric linear additive mixed model. However, it is worth noting that Graham and Dender (2011) do not apply specific adjustments for endogeneity in their model. Instead, they carry out their analysis on various sub-samples of the data by ‘area type’ to limit the influence of confounding factors.

In another study, Le Néchet et al. (2012)[86] explore the presence of such non-linearities with French data. The adopted approach is similar to Graham and Dender (2011), however, the authors do address concerns related to the endogeneity of the agglomeration variable using valid instrumental variables. The analysis again reveals considerable nonlinearity in the relationship of interest. Following from their results, the authors highlight that conventional country-level aggregate elasticity estimates are likely to misrepresent the actual magnitude of the productivity benefits from agglomeration.

In an ongoing study, Anupriya et al. (2023)[87] investigate the presence of non-linearities in the agglomeration-productivity relationship for six industry sectors in England using the Financial Analysis Made Easy (FAME) data. The study adopts a two-step approach to flexibly model the agglomeration-productivity relationship. The first step involves estimating the total factor productivity (TFP) of a firm by constructing its production function. Within this step, the production function is estimated by making use of the panel control function of Ackerberg et al. (2006). The second step comprises regressing the estimated TFP values on the chosen measure of agglomeration (that is, ED). In particular, a Bayesian Non-parametric Instrumental Variables approach[88] is adopted to model the agglomeration-productivity in a fully flexible data-driven way while adjusting for potential spurious influences via the use of valid instrumental variables within a control function approach. Below, we describe the key steps in the calculation.

In the first step, the production of outputs Y_{ict}^{s} by a firm i in industry sector s in area c and year t is modelled using a Cobb Douglas function, with factor inputs capital K_{it}^{s}, labour L_{it}^{s} and materials M_{it}^{s}; as covariates:

$$\log Y_{ict}^{s} = \beta_{k}^{s} \log K_{ict}^{s} + \beta_{l}^{s} \log L_{ict}^{s} + \beta_{m}^{s} \log M_{ict}^{s} + \omega_{ict}^{s} + \gamma_{t}^{s} + e_{ict}^{s}$$

where β_{k}^{s}, $\beta_{l}^{s}$and β_{m}^{s} are the parameters of the production function. ω_{ict}^{s} is the unobserved efficiency or productivity of the firm, commonly referred to as its TFP. It represents the efficiency level that remains unobserved by the analyst but is known to (or predicted by) the firm. γ_{t}^{s} are year dummies that capture the year-specific effects on productivity and inflation. e_{ict}^{s} is a normally distributed idiosyncratic error term, or in other words, all random shocks to the outputs.

In the second step, the causal impact of agglomeration on productivity is estimated via modelling the estimated TFP $\widehat{\omega}_{ict}^{s}$ as a fully flexible function of the agglomeration measure ρ_{ct}^{s} indicating the ED of the zone c where the firm i is located:

$$\widehat{\omega}_{ict}^{s} = S^{s}(\rho_{ct}^{s}) + \eta_{ct}^{s} + u_{it}^{s} + \xi_{ict}^{s}$$

where η_{ct}^{s} and u_{it}^{s} consists of unobserved area effects and unobserved firm effects, respectively, both of which are correlated with ρ_{ct}^{s}. ξ_{ict}^{s} represents an idiosyncratic error term capturing all random shocks to the dependent variable. The exact structural form of how ρ_{ct}^{s} enters the equation is unknown, so a non-parametric specification is adopted $S^{s}(.)$, the shape of which is delivered by the data via use of regression splines.

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86 Le Néchet, F., Melo, P. C., & Graham, D. J. (2012). Transportation-induced agglomeration effects and productivity of firms in megacity region of Paris basin. *Transportation research record*, *2307*(1), 21-30.

87 Anupriya, Graham, D.J., & Bansal, P. (2023). Testing for non-linearity of agglomeration effects. Working paper: Imperial College London.

88 Wiesenfarth, M., Hisgen, C. M., Kneib, T., & Cadarso-Suarez, C. (2014). Bayesian nonparametric instrumental variables regression based on penalized splines and dirichlet process mixtures. *Journal of Business & Economic Statistics*, *32*(3), 468-482.

The study delivers three crucial insights:

a) There is presence of statistically significant non-linearities in agglomeration effects across all six industries.

b) There exists a critical mass of agglomeration beyond which the positive benefits of agglomeration on productivity are observed and, in most cases, a threshold beyond which the agglomeration effects either become statistically insignificant or negative.

c) Agglomeration elasticities delivered by the adopted model take more extreme values than ones derived from a log-linear model of productivity and agglomeration.

Further, the study also delivers interesting insights on the spatial distribution of agglomeration effects across the six industries by mapping the estimated agglomeration elasticities to the different zones based on their ED levels. The approach adopted in Anupriya et al. (2023) is worthy of further investigation for the re-estimation of agglomeration parameters for TAG. It is worth highlighting though that, in a two-step approach, omission of effective density from the first step regression may lead to biased estimates of the TFP. To minimise OVB concerns, it is crucial that the production function estimation in the first step is done with suitable corrections for endogeneity. Nonetheless, as Graham and Gibbons (2019) suggest, one-step estimates are likely to be more efficient than two-step ones.

4.6.3 Conclusions and recommendations

The key points made in this section are as follows.

- Most existing studies pre-specify the agglomeration-productivity relationship using a log-linear functional form, which implies a concave and non-decreasing function in levels.
- Nevertheless, this functional form approximation seems inconsistent with economic theory that predicts the marginal returns to agglomeration to decrease with city size, for instance, due to higher congestion and land costs in denser cities.
- It has, in fact, been pointed out that the agglomeration-productivity relationship should be concave and bell-shaped curve, owing to the interplay between the costs and benefits of agglomeration. This implies that effect of city scale can be heterogeneous across ranges of agglomeration, with positive and negative gradients, thresholds, and flat regions across the range. Interestingly, there is now some empirical evidence in the literature that confirms such hypotheses.
- Consequently, it is important that the agglomeration model is flexible enough to capture the presence of non-linearities of agglomeration effects. Two step approaches; where total factor productivity (TFP) is obtained from the production function in a first stage model, and the predicted values of TFP then regressed on agglomeration and other spatial variables in a second stage regression; allow for more flexibility in modelling the agglomeration-productivity relationship, including application of non-parametric or semi-parametric causal methods.

The section concludes with the following recommendation for future work.

R9 The econometric model of agglomeration should be designed to capture potential non-linearities of agglomeration effects, which can be achieved by flexibly modelling the agglomeration-productivity relationship using non-parametric or semi-parametric regression. Implications of the results for appraisal should be evaluated.

4.7 Heterogeneity in parameters

R10	**Recommendation: Econometric models that can yield heterogeneous agglomeration effects by area type, by functional classification of firms, and by trip purpose should be estimated, for instance, by estimating separate agglomeration elasticities for relevant sub-samples of the data. The suitability of the resulting estimates for use in appraisal should be assessed.**

The two-step calculations of the transport induced WEIs of agglomeration outlined in Section 3.2 considers a single, aggregated productivity elasticity η_{ω,ρ^d}. It is, instead, possible to allow for heterogeneous responses of productivity to agglomeration within the econometric model, thus yielding potentially different elasticities for different sub-groups.

4.7.1 Exploring the existence of heterogeneous agglomeration effects

A straightforward approach is to calculate separate agglomeration elasticities for relevant sub-samples of the data. For instance, several previous studies including Graham et al. (2009) and Le Néchet et al. (2012) have estimated separate agglomeration elasticities for different industry sectors from industry-wise sub-samples of the data. As mentioned in Section 3.3, such an approach allows an assessment of the role of local industrial structure in observed urbanisation effects.

Relatedly, Graham and Van Dender (2011) suggest that need not be assumed homogeneous across zones. In their study, Graham and Van Dender (2011) estimate separate agglomeration elasticities for sub-samples of the data based on area type to reveal heterogeneity in the responsiveness of productivity to ATEM. In particular, they adopt the DfT classification on area type that allocates small zones in the UK to three broad groups: (i) national centre (subdivided into central, inner and outer London), (2) regional centres (subdivided into inner and outer conurbations), and (3) sub-regional centres (comprising urban big, urban medium and urban small areas, with populations greater than 250,000, 100,000 and 25,000, respectively).

Another study by Békés and Harasztosi (2013)[89], explored such heterogeneity in the context of trading versus non-trading firms. Following from the international trade literature, they argue that the two categories of firms are different in terms of their workforce, size, and productivity, and therefore, may exhibit heterogeneity in agglomeration effects. Using Hungarian manufacturing firm level data from 1992 to 2003 for 150 micro-regions, they do find the agglomeration elasticity is for traders to be substantially larger than for non-traders. Similarly, Anderson and Lööf (2011)[90] reveal heterogeneity in agglomeration effects by firm size (number of employees) for manufacturing firms in Sweden.

Where the size of the dataset is small and, as a result, consistent estimation of agglomeration elasticities within each subsample is not possible, heterogeneity can be quantified by including interactions of the agglomeration covariate with category-specific dummy variables in the agglomeration model. Maré and Graham (2013)[91] adopt this approach to estimate agglomeration elasticities by industry and region, in particular, by interacting the ATEM measure with industry and region dummies, respectively, in their model.

Another important area of research could be to explore distinction in agglomeration elasticities by trip purpose, for instance, commuting versus non-commuting. Such a distinction could allow contributions from the sources of agglomeration to be distinguished, for instance, productivity benefits arising from commuting trips can be linked to labour market effects.

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[89] Békés, G., & Harasztosi, P. (2013). Agglomeration premium and trading activity of firms. *Regional Science and Urban Economics*, *43*(1), 51-64.

[90] Andersson, M., & Lööf, H. (2011). Agglomeration and productivity: evidence from firm-level data. *The annals of regional science*, *46*, 601-620.

[91] Maré, D. C., & Graham, D. J. (2013). Agglomeration elasticities and firm heterogeneity. Journal of Urban Economics, 75, 44-56.

It is worth emphasising this theme remains unexplored in the literature as data on trips classified by purpose have been traditionally unavailable as a spatial panel. However, more recently, mobile network datasets[92] [93], enriched with other GPS-based data sources have emerged as a promising alternative.

4.7.2 Incorporating heterogeneous agglomeration effects in TAG calculations

To allow for heterogeneity, the calculations described in Section 3.1 can be extended as follows. In the first step, GTC based changes in economic density ($d\ \log \rho_{i,s}^{\bar{g}}$) should be predicted for each sub-sample s, for instance, by reconstructing the ED measure as follows:

$$\rho_{i,s}^{\bar{g}} = \sum_{j=1}^{n} m_{j,s} \cdot f(\bar{g}_{ij})$$

where $m_{j,s}$ is a measure of economic mass at zone j in sub-sample s and $f(.)$ is a decreasing function of the mean modal GTC of travelling from i to j. In the second step, distance-based ATEM elasticities (η_{ω,ρ^d}^{s}) for each sample s should be measured using the ED measure

$$\rho_{i,s}^{D} = \sum_{j=1}^{n} \frac{m_{j,s}}{d_{ij}^{\alpha}}$$

where d_{ij} is the Euclidean distance between zones i and j and α is a parameter that determines the decay of agglomeration impacts over space.

Using the two quantities described above, the transport induced WEIs of agglomeration (for instance, impacts on productivity) can be computed as

$$d\ \log \omega = \sum_{s} \sum_{i=1}^{n} \eta_{\omega,\rho^d}^{s} \times d\ \log \rho_{i,s}^{\bar{g}}$$

4.7.3 Conclusions and recommendations

The key points made in this section are as follows.

- It is possible to allow for heterogeneous responses of productivity to agglomeration within the econometric model, thus yielding potentially different elasticities for different sub-groups.
- The most straightforward approach to achieve this objective is to calculate separate agglomeration elasticities for relevant sub-samples of the data. Another possible approach involves interacting the adopted ATEM measure with category-specific dummy variables to quantify heterogeneity by relevant categories.
- Estimation of distinct agglomeration elasticities by industry type is popular in the literature but exploring heterogeneity in the responsiveness of productivity to agglomeration by area type, by functional characteristics of firms, and by trip purpose are also worth exploring.

The section concludes with the following recommendation for future work.

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[92] Li, Z., Xiong, G., Wei, Z., Zhang, Y., Zheng, M., Liu, X., Tarkoma, S., Huang, M., Lv, Y., & Wu, C. (2021). Trip purposes mining from mobile signaling data. *IEEE Transactions on Intelligent Transportation Systems*, *23*(8), 13190-13202.

[93] Alexander, L., Jiang, S., Murga, M., & González, M. C. (2015). Origin–destination trips by purpose and time of day inferred from mobile phone data. *Transportation research part c: emerging technologies*, *58*, 240-250.

R10 Econometric models that can yield heterogeneous agglomeration effects by area type, by functional classification of firms, and by trip purpose should be estimated, for instance, by estimating separate agglomeration elasticities for relevant sub-samples of the data. The suitability of the resulting estimates for use in appraisal should be assessed.

4.8 Differential elasticities by mode and the role of active travel

R11 Recommendation: Due to econometric challenges arising from severe multicollinearity, estimating mode specific agglomeration elasticities is not recommended.

The TAG calculations of the WEIs of agglomeration described in Section 3.1 assumes that agglomeration determines productivity via the model: $\omega_i = f\left(\rho_i^D, Z_i\right)$, where ω_i signifies productivity (TFP) in location i, ρ_i^D is a distance-based ED, and Z_i signifies a composite term comprising other factors determining TFP.

4.8.1 Incorporating mode-specific agglomeration effects within TAG

As Graham and Gibbons (2019) suggest, the above model can be generalised using GTC-based ED disaggregated by mode, as follows:

$$\omega_i = f\left(\rho_i^1, \ldots, \rho_i^K, \rho_i^1, Z_i, A_i\right),$$

where $\rho_i^k, k = (1, \ldots, K)$, captures the agglomeration effects arising from travel via mode k, and A_i represents non-transport related agglomeration effects on productivity. The existing ED measure from TAG can be extended to represent modal agglomeration, ρ_i^k, as follows:

$$\rho_i^k = \sum_{j=1}^{n} \frac{\theta_{ijk}(g_{ij}) m_j}{g_{ijk}^{\alpha}} = \sum_{j=1}^{n} \rho_{ij}^k$$

where $\theta_{ijk}(g_{ij})= \theta_{ijk}\left(g_{ij1}, \ldots, g_{ijK}\right)$ is the mode share on link ij, which is a function of the GTCs on that link.

Following from the above equation, the elasticity of ρ_i^k with respect of the GTC of mode k on link ij is

$$\eta_{\rho_i^k, \log g_{ijk}} = \frac{\partial \ \log \rho_i^k}{\partial \ \log g_{ijk}} = \left(\frac{\partial \ \log \theta_{ijk}(g_{ij})}{\partial \ \log g_{ijk}} - \alpha\right) \frac{\rho_{ij}^k}{\rho_i^k}$$

and with respect to mass at location j is

$$\eta_{\rho_i^k, \log m_j} = \frac{\partial \ \log \rho_i^k}{\partial \ \log m_j} = \frac{\rho_{ij}^k}{\rho_i^k}$$

Thus, the proportional change in productivity generated agglomeration externalities, holding everything else constant, can be calculated as:

$$d \ \log \omega = \sum_{i=1}^{n} \sum_{k=1}^{K} \eta_{\omega, \rho^k} \left(\sum_{j=1}^{n} \eta_{\rho_i^k, \log m_j} \ d \log m_j \ + \sum_{j=1}^{n} \eta_{\rho_i^k, \log g_{ijk}} d \log g_{ijk} \right)$$

with parameters η_{ω,ρ^k} estimated from a single productivity regression model.

4.8.2 Practicalities surrounding calculation of mode-specific agglomeration elasticities

Utilising mode elasticities as above are attractive due to their apparent ability to closely align with the kinds of accessibility alterations commonly assessed in transport appraisals. However, while such calculations are, in theory, possible to do, it is extremely difficult to empirically obtain separate mode specific elasticities.

This is because mode-specific EDs, constructed using identical mass measures for each mode, tend to be highly correlated, thereby leading to issues of severe multicollinearity when estimating multiple mode-specific elasticities, $\eta_{\omega,\rho^1}, \ldots, \eta_{\omega,\rho^K}$ via a single regression model. Graham and Gibbons (2019), therefore, recommend against estimating mode-specific agglomeration elasticities.

It is worth emphasising that agglomeration economies experienced by firms or workers located in a certain area, is eventually determined by the overall accessibility of that area, instead of being determined by distinct modes of transport. Therefore, it is more meaningful to assess to what extent various modes of transport contribute to accessibility, however, defining mode-specific separate elasticities may not add much value.

Rather than using mode-specific ED variables within a single regression function it is, of course, possible to average them into a single measure, for example, as weighted sums of travel time components and travel costs, with weights estimated from behavioural data. For instance, Börjesson et al. (2019)[94] use mode shares are weights to develop their averaged GTC-based agglomeration measure.

One possible benefit of the weighted metric is that by capturing additional variance in mode shares it renders representation of agglomeration less persistent over time and emphasises cross-sectional differences, thus potentially providing more scope for identification.

An appropriate productivity model could be: $\omega_i = f\left(\rho_i^{\bar{g}}, Z_i, A_i\right)$, and the corresponding productivity calculation, holding A and Z constant, can proceed as:

$$d\ \log\omega = \sum_{i=1}^{n}\eta_{\omega,\rho^{\bar{g}}}\left(\sum_{j=1}^{n}\eta_{\rho_i^{\bar{g}},\log m_j}\ d\log m_j\ + \sum_{j=1}^{n}\eta_{\rho_i^{\bar{g}},\log\overline{g_{ij}}}d\log\overline{g_{ij}}\right)$$

where $\eta_{\omega,\rho^{\bar{g}}}$ represents the elasticity of productivity with respect to average GTC-based ED.

Using the productivity model defined above, the contribution of a specific mode m to overall productivity can then be assessed as:

$$\frac{\partial\log\omega}{\partial\log\bar{g}_m} = \frac{\partial\log\omega}{\partial\log\bar{g}}\times\frac{\partial\log\bar{g}}{\partial\log\bar{g}_m}$$

where the second term on the right-hand side can be obtained from a transport model.

Note, however, that to construct a single ED GTC-based measure, assumptions are required with respect to including time-of-day variance in GTCs across modes and addressing the issue of zero entries in OD matrices resulting from the lack of an option to travel along certain links in the network by a given mode.

Moreover, as discussed previously, the fundamental approach to calculating WEIs needs to be altered for GTC based elasticities to be validly used in empirical calculations of agglomeration effects.

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[94] Börjesson, M., Isacsson, G., Andersson, M., & Anderstig, C. (2019). Agglomeration, productivity and the role of transport system improvements. *Economics of Transportation*, *18*, 27-39.

It is worth noting that, there has been some recent interest in understanding the role of active travel in driving the economic benefits of agglomeration. Rosenthal and Strange (2003) suggest that information spillovers (learning) that require frequent contact between workers dissipate over a short distance as walking to a meeting place becomes difficult. Harvey (2019)[95] note this finding as empirical evidence in support of walking trips being an important source of learning agglomeration economies. Relatedly, Rohani and Lawrence (2017)[96] find strong positive associations between walking connectivity and labour productivity in Auckland's city centre. While such associations may be interesting, obtaining mode-specific agglomeration elasticities is an extremely challenging. We, therefore, advise against attempts to estimate distinct agglomeration elasticities for active travel.

4.8.3 Conclusions and recommendations

The key points made in this section are as follows.

- In theory, the current TAG calculations can be extended to include mode-specific agglomeration effects. However, mode-specific EDs constructed using identical mass measures for each mode tend to be highly correlated, thereby leading to issues of severe multicollinearity when estimating multiple mode-specific elasticities in a single regression model.
- Moreover, the economic benefits of agglomeration for firms and workers hinge more on the overall accessibility of their location than on individual transport modes, making the assessment of how various transport modes enhance accessibility more relevant than quantifying their specific contributions.

The section concludes with the following recommendation for future work.

R11 Due to econometric challenges arising from severe multicollinearity, estimating mode specific agglomeration elasticities is not recommended.

[95] Harvey, M. (2019). The role of distance decay in estimating wider economic benefits from agglomeration. In *Australasian Transport Research Forum (ATRF), 41st, 2019, Canberra, ACT, Australia*.
[96] Rohani, M., & Lawrence, G. (2017). The Relationship between Pedestrian Connectivity and Economic Productivity in Auckland's City Centre. Network Scenarios Analysis.

5. Benchmark modelling

In this section we propose a complementary quantitative method to improve the robustness of the estimation and use of agglomeration elasticities in transport appraisal. It is a common practice in empirical research to perform supplementary numerical simulations with the aim of replicating the empirical exercise in a controlled environment. Similarly, in theoretical research, the strengths and weaknesses of partial equilibrium transport models are useful to test by benchmarking their policy predictions against an equivalent general equilibrium model which includes a wider set of decision margins (relocation, for example) and potential distortions in non-transport markets. We build on these practices by proposing the application of a spatial computable general equilibrium (SCGE) model with three core objectives:

a) To implement a synthetic data generation process in which statistical endogeneity such as omitted variable bias is introduced in a controlled manner, for example by assuming that one of the variables of the SCGE model is unobserved in reality. Thus, the effectiveness of the statistical approaches proposed in previous sections can be tested transparently.

b) To compare the outcomes of the methodology of partial equilibrium appraisal, including Wider Economic Impacts, against the welfare measures of an SCGE model. This enables us to quantify the potential threats of double counting and other losses stemming from the partial equilibrium assumption.

c) In a more detailed comparison, each of the three levels of the TAG methodology can be benchmarked against a consistent simulation framework.

To the best of our knowledge, the existing academic literature on transport appraisal does not report similar efforts achieving both objectives.[97]

In the context of transport appraisal in the UK, the model proposed in this section classifies as a supplementary economic model (SEM). TAG Unit M5.3 defines SEMs as "non-standard methods to estimate the economic impact of transport schemes". In particular, such models are used to "assess how transport schemes impact on the spatial distribution of the economy", noting that "the challenges associated with appraising these impacts and the difficulty of validating these models, they should be used to supplement rather than replace conventional appraisal methods". Widely used SEM approaches include Land-Use Transport Interaction (LUTI) models and SCGE, while recent advances in spatial economics offer promising future applications of quantitative spatial models (QSM) that we also rely on this section.

Within the scope of this study, we explore the potential use of a benchmark SCGE model to a limited extent. In this section we demonstrate this idea in a simple baseline version of an SCGE model that handles a small subset of the full range of potential empirical challenges covered earlier in the report. Future research should explore a path through which this baseline model can extended to capture the micro-mechanisms behind WEIs more comprehensive.

It is important to emphasise before delving into more technical details that a benchmark SCGE model, and the synthetic data generating process built on it, are by no means a proven representation of ground truth. Just like other models, SCGE models are based on strong assumptions and our current understanding of the functioning of urban economies. Thus, the fact that an empirical method or a partial equilibrium appraisal approach passes the test we impose in this exercise does not imply that these simplified tools unambiguously comply with 'reality'. However, the benchmarking exercise may help us identify potential flaws and/or improve our confidence in the workhorse appraisal methodology.

The discussion proceeds according to the following steps. Section 5.1. introduces the properties of the baseline SCGE model and explains the extent to which it exceeds the capabilities of partial

[97] Limiting our attention to theoretically motivated studies, a notable example is Eliasson and Fosgerau (2019) who develop an SCGE model to quantify the potential double counting of matching benefits, a part of the full range of agglomeration economies. However, their model was not applied as a synthetic data generator to test empirical methods.

equilibrium appraisal through endogenous location choice and interactions with the labour and housing markets. Section 5.2. explains the use of this SCGE model as a synthetic data generating process and shows, as an illustration, how synthetic data is mobilised to handle omitted variable bias in the estimation of agglomeration elasticities. Section 5.3. simulates hypothetical transport improvements in the baseline SCGE environment and compares the results of the current TAG partial equilibrium appraisal against the welfare measure produced by the general equilibrium model. Finally, Section 5.4. concludes with some discussion and an agenda for future work.

5.1 Model development and calibration

The academic literature on SCGE modelling offers a variety of alternative approaches that can be adapted for the present purposes. See extensive reviews of the field in Robson et al.[98] and Sahraki and Bachmann,[99] for example. The illustrative model we present here has numerous attractive properties, including quick convergence, simple functional forms, and the fact that it captures agglomeration economies through a function that makes firm productivity dependent on economic density. However, given the abundance of alternative SEM models, it remains an open question to decide which approach is most suitable as a benchmarking tool in a transport appraisal context.

The model is a combination of a traditional representation of commuter behaviour, with separate time and money budget constraints (see, for instance, Anas and Liu[100]), and the Fréchet discrete choice specification frequently used in the recent quantitative spatial economics literature following the pioneering urban model of Ahlfeldt et al.[101] The model captures the behaviour of three groups of agents, as depicted in Figure 1.

a) Households: They observe the distribution of wages, final consumer prices and residential housing prices in space, the cost of commuting, and they have idiosyncratic preference for living and working in certain locations. The solution of their utility maximisation problem yields optimal consumption and floorspace demand functions, the amount of labour supplied, and a probability associated with the choice of each residence-workplace pair available in the model.

b) Urban production is represented by a location-specific production function using two inputs: labour and commercial floorspace.[102] We assume profit maximisation, perfect competition and constant returns to scale, so that the equilibrium goods prices and factor demand levels satisfy a zero-profit condition. The production function has a productivity (i.e. total factor productivity, TFP) term, which captures both the exogenous geographical characteristics and the impact of agglomeration economies through a measure of access to economic mass (ATEM) and an agglomeration elasticity.

c) The amount of floorspace supply in a given location is determined by the profit-maximising behaviour of a construction sector under perfect competition. That is, construction firms use land and capital to produce floorspace, and the equilibrium floorspace supply leads to zero profits under the prevailing prices in the real estate market.

The behaviour of the three groups of agents is interlinked through three market clearing conditions. The labour market clears when the equilibrium wage vector (i.e., specific wage values associated with each workplace) equates the supply and demand of labour. In the goods market we assume that intra-urban trade is costless, so the market-clearing price of the consumer good is the same in all locations and ensures the balance of supply and demand. The prices of commercial and residential floorspace differ in the model by a constant ratio to reflect differences in how these are

[98] Robson, E. N., Wijayaratna, K. P., & Dixit, V. V. (2018). A review of computable general equilibrium models for transport and their applications in appraisal. *Transportation Research Part A: Policy and Practice*, *116*, 31-53.

[99] Shahrokhi Shahraki, H., & Bachmann, C. (2018). Designing computable general equilibrium models for transportation applications. *Transport Reviews*, *38*(6), 737-764.

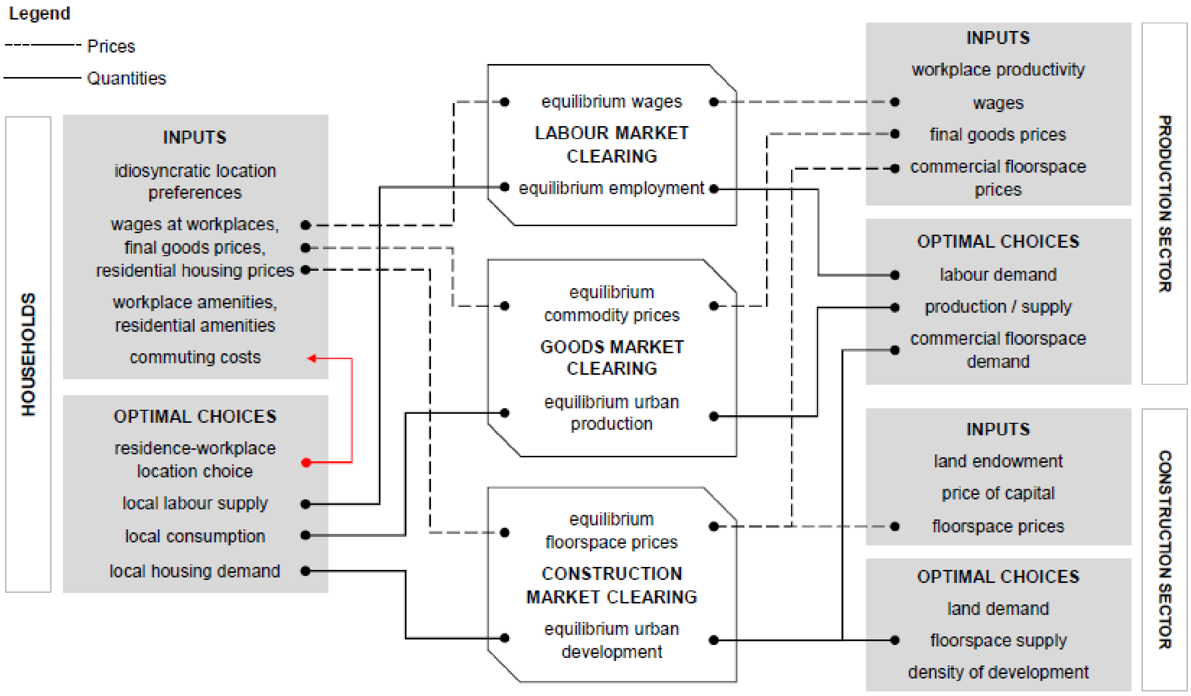
[100] Anas, A., & Liu, Y. (2007). A regional economy, land use, and transportation model (relu‐tran©): formulation, algorithm design, and testing. *Journal of regional science*, *47*(3), 415-455.

[101] Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica*, *83*(6), 2127-2189.

[102] Future extensions of this model could include business/freight transport as a factor in the production function explicitly, as already suggested in the empirical context in Section 3.1.3.

taxed and regulated. Within this constraint, the pair of floorspace price vectors equates the demand of households and firms with floorspace construction.

Figure 2: Schematic layout of the urban equilibrium model adapted to benchmarking exercises



5.1.1 Functional forms

Let w_j, q_i and p_i denote wages, residential floorspace prices and consumer prices. The (indirect) utility associated with residential location i and workplace j is

$$u_{ij} = u_{ij}(w_j, q_i, p_i, t_{ij}, \tau_{ij}),$$

where t_{ij} and τ_{ij} are the duration and monetary price of commuting. An important feature of this SCGE model is that wages and consumption and floorspace prices are not the only determinants of location choices. The heterogeneity in local geographical characteristics is captured by three vectors of location fundamentals. These are (i) amenities for residential land use X_i, (ii) amenities for workplaces E_j, and (iii) a fundamental determinant of local productivity, a_j. Local amenities may capture access to recreational facilities, green space, and scenic views, for example. Given these fundamentals and that households' heterogeneous taste is represented by a Fréchet-distributed utility shock with a shape parameter ε, the probability that a worker decides to live in i and work in j is

$$\lambda_{ij} = \frac{X_i E_j \cdot u_{ij}^{\varepsilon}}{\sum_r \sum_s X_r E_s \cdot u_{rs}^{\varepsilon}}.$$

Another important technical detail of the model is the specification of urban production, capturing agglomeration economies. We assume a Cobb-Douglas production function

$$Y_j = A_j(\rho_j) \cdot M_j^{\alpha} \cdot H_j^{1-\alpha},$$

in which M_j is the effective labour supply in location j, H_j is the commercial floorspace input, and $A_j(\rho_j)$ is a measure of total factor productivity, and agglomeration-dependent shifter of the production function. The latter is the product of the local geographical determinants of productivity and the effective density in location j with agglomeration elasticity η.

$$A_j(\rho_j) = a_j \cdot \rho_j^{\eta}$$

Effective density, or access to economic mass (ATEM), can be defined in multiple ways, and future research should explore the sensitivity of the analysis with respect to this functional form. In the following illustrative examples, we adopt a negative exponential specification.

$$A_j = a_j \left[\sum_s \exp(-\delta \cdot gt_{sj}) \, M_s \right]^\eta$$

This ATEM measure sums labour supply M within location j as well as the surrounding locations with a multiplier that converges to zero as the generalised travel time gt_{sj} increases from j. The pace of distance decay is controlled by parameter δ. The detailed specification of the model is provided in the Technical Appendix.

5.1.2 Calibration and spatial layout

Parameter calibration plays a key role when an SCGE model is applied to predict the future spatial outcome of a policy and derive economic evaluation measures. In the current application we use the model to generate synthetic data that is consistent with economic theory and then test whether a proposed empirical method is able to recover some of the model parameters that we treat unobserved during the test. Model calibration is not so crucial in this case. Nevertheless, we select input parameters from another application of the same model[103] that we quantified using Local Authority District level data from London.

We keep the model's spatial layout general by considering N^2 locations arranged into the nodes of a regular $N \times N$ grid network. Panel A of Figure 2 depicts this layout for $N^2 = 100$ randomly generated locations. The land area of these locations is assumed to be homogeneously distributed such that total land area equals that of the administrative area of Greater London. The times and monetary expenditures of travel along the graph's edges are also homogeneous: movements between neighbouring nodes cost 15 minutes and one monetary unit. It would be easy to introduce more randomness in these input parameters but, after multiple attempts, we decided to keep land areas and travel costs homogeneous to improve the interpretability of the simulation outcomes.

[103] Hörcher, D., & Graham, D. J. (2023). Endogenous commuting time valuations and the leisure-labour trade-off in quantitative spatial modelling. Working Paper, Imperial College London.

Figure 3: Exogenous location characteristics (panels A to D) and some of the associated simulation outcomes (E, F). Units in brackets where applicable.

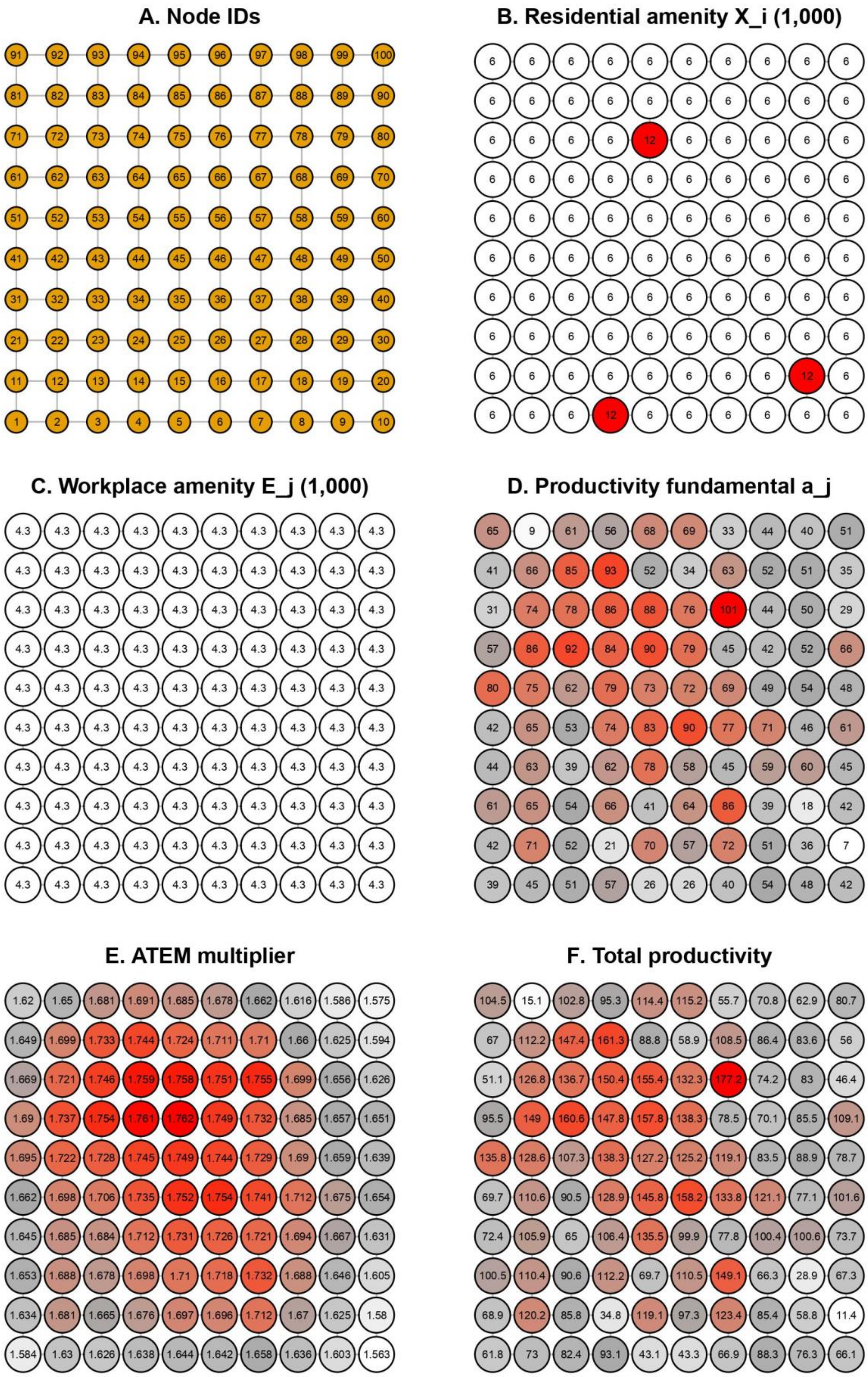
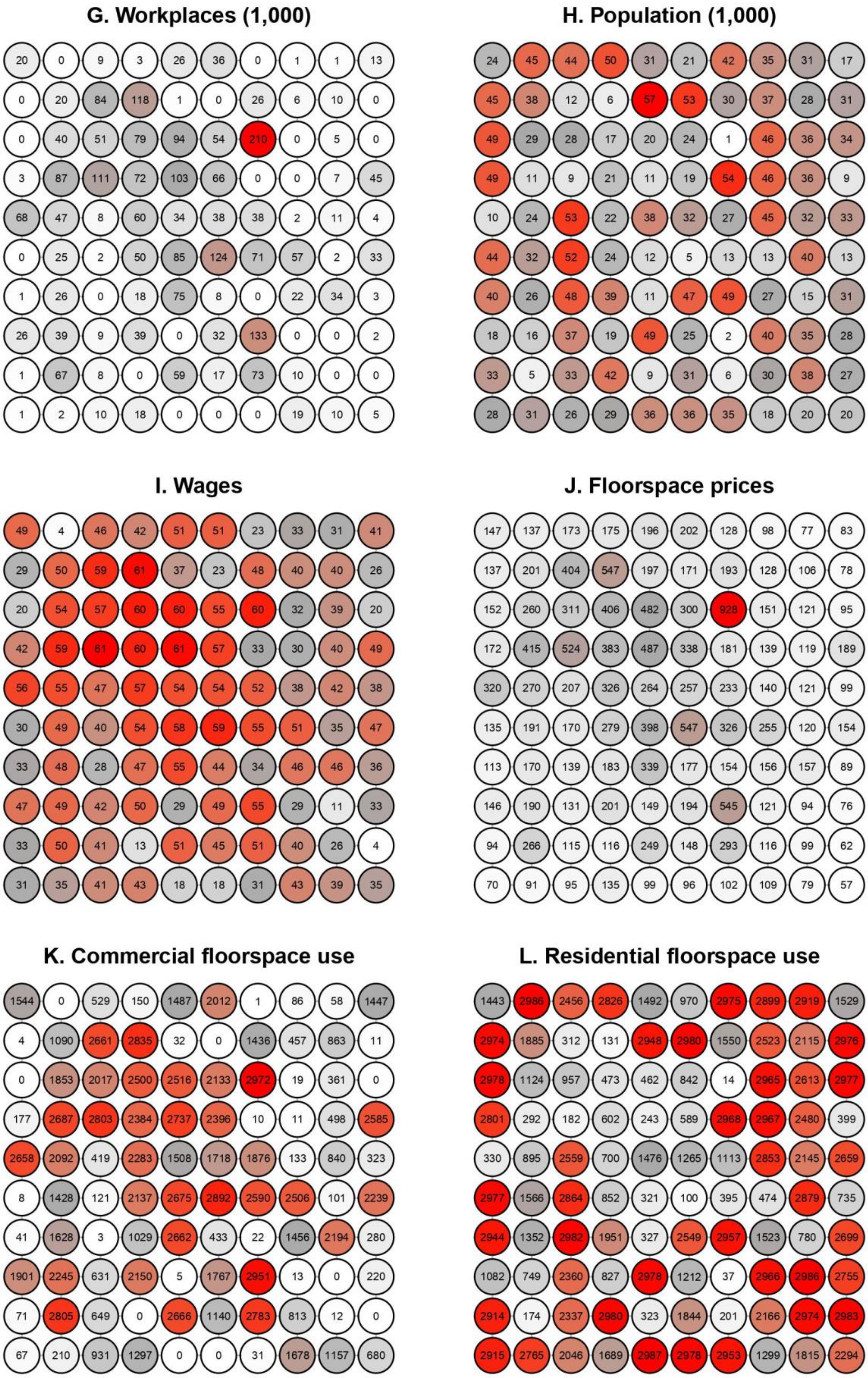


Figure 4: Further equilibrium outcomes based on the geography shown in Figure 3. Units in brackets where applicable.



The distribution of location fundamentals is another dimension in which real cities show considerable heterogeneity. Once again, we decided to take a simple approach in parameter generation to achieve interpretable results. As Panel B of Figure 3 illustrates, residential amenity levels are equal across locations and we select two nodes randomly which become particularly attractive as a residence. This introduces some variance in residential location choices. After several experiments, we neutralise workplace amenities in the model to make sure that wages and the underlying productivity advantages become the main driving force behind workplace choices, as the latter becomes the main focus of our empirical application. Nevertheless, in more complex future applications it will be an interesting empirical challenge to separate the effect of pure workplace amenities from agglomeration economies capitalised in wages.

The distribution of the productivity fundamental is crucial in the present analysis. This variable will remain unobserved in the empirical part in Section 5.2. We generate the a_j values partly randomly to ensure sufficient variation in the statistical model. However, omitted variable bias does not emerge if this unobserved variable is uncorrelated with the main variable of interest, ATEM. Thus, to ensure some correlation, we generate the random a_j pattern such that it correlates with the concentric ATEM distribution but is somewhat skewed towards the North-West of graph layout.

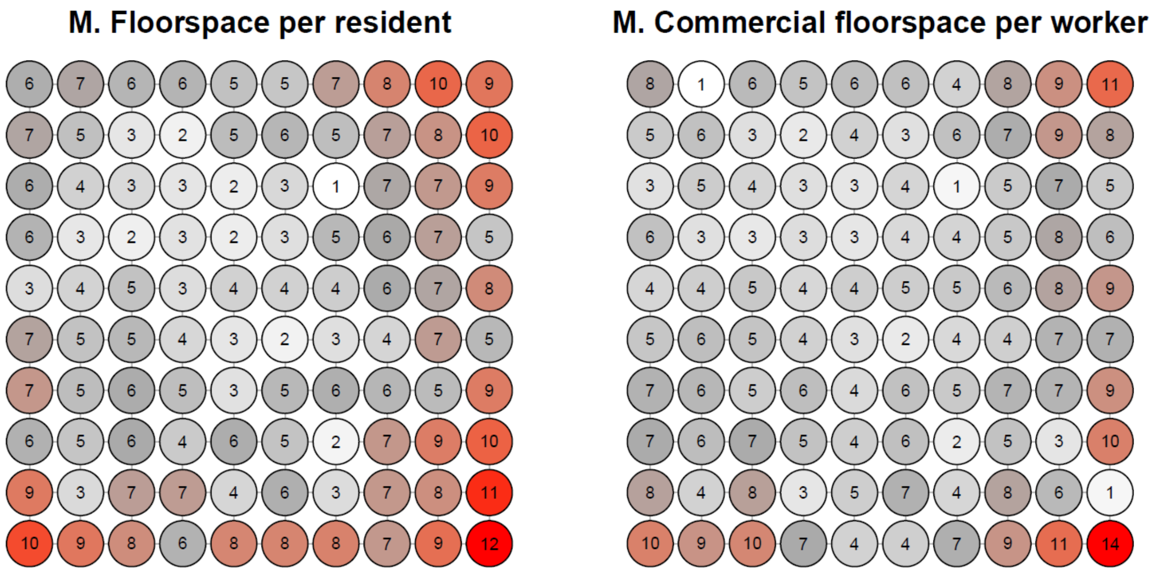
5.1.3 Equilibrium outcomes

Panels E to N of Figures 4 and 5 show several angles of urban economic outcomes after the general equilibrium algorithm converges. Panel E highlights that even though the underlying productivity fundamentals (Panel D) are asymmetric and clearly skewed towards the North-West of the layout, ATEM remains remarkably concentric, simply due to the geometric fact that peripheral locations have fewer neighbouring nodes to consider in the ATEM calculation (for a decomposition of this centrality effect in ATEM se Graham and Gibbons 2015). This property prevails even if we begin with a uniformly distributed a_j vector. Panel E is the ATEM multiplier, that is, ρ_j^{η}, which is essentially the magnitude by which agglomeration shifts the production function. Panel F is $a_j \cdot \rho_j^{\eta}$, the product of Panels D and E.

The distribution of workplaces in Panel G follows the distribution of productivity for obvious reasons, although employment often drops to zero in peripheral locations where the fundamental productivity was low. As intuition suggests, employment is more concentrated in central locations, but even in that region there is substantial diversity governed by two reasons. The first one is the fluctuation of productivity. Second, we observe complementarity between workplaces and residences which indicates competition for floorspaces between the two land uses. Panel G shows that peripheral (suburban) locations are more attractive as a residence than as a workplace, but some of the central zones may also accommodate a significant concentration of residences. This is because the ideal residential locations are both affordable and close to major employment centres to reduce the cost of commuting. Thus, we observe in multiple cases that the immediate neighbour of a major workplace locations specialises to (high-density) residential use. We believe this is a realistic outcome of the model. Comparing Panels F and I reveals that the equilibrium wages are closely correlated with urban productivity. Similarly, floorspace prices in Panel J follow the pattern of workplaces in Panel G.

Figure 5 provides further simulation outcomes on the (inverse) density of floorspace use throughout the synthetic city. Panel N shows the equilibrium demand for residential floorspace among households while Panel M depicts the same metric for commercial floorspace. The two patterns are similar. In line with the theoretical predictions of monocentric city models, households and firms located closer to the city edge consume more floorspace on average. This is a natural consequence of lower land and floorspace prices in these areas caused by lower accessibility and milder competition for space.

Figure 5: Housing densities in equilibrium, based on the geography shown in Figure 3



Our overall assessment is that the spatial outcomes depicted in Figure 3 to 5 confirm that our illustrative SCGE model is able to replicate realistic phenomena in urban economies.

5.2 Synthetic data generation and agglomeration estimation

The simulation outcomes presented above imply that we generated a sample of 100 observations, which are based on random input parameters but the relationship between them is governed by an economically coherent model. In particular, we derive values of the equilibrium output (Y_j), factor demand levels (M_j and H_j), and ATEM measures (ρ_j) for each location. Under the functional forms defined above, these data ensure a perfect fit for a log-linear transformation of our production function as well.

$$\log(Y_j) = \log(a_j) + \eta \log(\rho_j) + \alpha \log(M_j) + (1-\alpha)H_j$$

However, we assume that the exogenous location fundamental a_j is unobserved in a regular empirical estimation of η, i.e., it becomes an unobserved determinant of productivity. This implies that one can only estimate

$$\log(Y_j) = I + \eta \log(\rho_j) + \alpha \log(M_j) + \beta \log(H_j) + \epsilon_j, \qquad (1)$$

in which the error term ϵ_j may be correlated with multiple endogenous covariates. Thus, a naïve regression would lead to a biased estimate of η, the main variable of interest in this analysis. An identification strategy should ensure that endogeneity is removed and we recover a causal estimate of the agglomeration elasticity.

One of the potential solutions is that we instrument $\log(\rho_j)$ using a suitable variable which correlates with ATEM but does not impact the outcome variable through alternative channels, e.g. it is uncorrelated with the unobserved variable a_j. A series of empirical studies (see Combes and Gobillon,[104] for example) mobilise historical data and use past population distributions and transport networks to instrument present access to economic mass. Historic data are not universally available, however, and thus their use in transport appraisal might not be guaranteed.

Instead, first we test a geometric instrument, the distance of location j from the geometric centre of our network layout. As Panel E in Figure 3 shows, ATEM follows a broadly concentric pattern even

[104] Combes, P. P., & Gobillon, L. (2015). The empirics of agglomeration economies. In Handbook of Regional and Urban Economics (Vol. 5, pp. 247-348). Elsevier.

if the distribution of fundamental productivities is asymmetrical. This is simply because nodes closer to the city boundaries have fewer nearby nodes to consider in the effective density calculation. Thus, radial distance may be highly correlated with ρ_j while, due to the more random allocation of a_j, it may be less correlated with the omitted variable.

Second, the synthetic simulation environment enables us to construct a random variable with a predetermined level of correlation with existing vectors. That is, we can create an artificial random variable with a low level of correlation with a_j and high correlation with ρ_j, with some numerical limitations given by the pre-existing relationship between these variables. The *faux* package[105] of R provides a stochastic algorithm to perform this task.

In summary, this numerical approach allows us to simulate a data generating process in which the spatial layout of locations and the transport network connecting them are partly randomly generated, but the relationship between the economic outcomes is consistent with microeconomic theory. Thus, we can test the empirical methodologies on a dataset that resembles real observations more closely than a completely randomly generated data.

Table 4: Illustrative regression results. The synthetic dataset was generated in the simulation by setting η=0.044.

	Dependent variable: log production			
	(1)	(2)	(3)	(4)
	OLS	2SLS	2SLS	2SLS
log(ATEM)	0.0897***	0.0629***	0.0298***	0.0503***
	(0.0109)	(0.0120)	(0.0125)	(0.0058)
log(labour supply)	**P**	**P**	**P**	**P**
log(floorspace use)	**P**	**P**	**P**	**P**
IV ATEM: radius			**P**	**P**
IV ATEM: synthetic		**P**		**P**
R^2	0.99	0.99	0.99	0.99
Sample size	100	100	100	100

Note: Standard errors in parentheses. *** p < 0.01

Table 4 shows the results of our illustrative empirical analysis based on the synthetic data derived from the general equilibrium outcomes described in the previous section. The dataset is generated with an agglomeration elasticity of $\eta = 0.044$, the parameter recommended in TAG. We estimate equation (1) in four specifications and the main variable of interest detailed in the table is $\hat{\eta}$. Column (1) is a naïve OLS model in which we ignore endogeneity. In model (2) we instrument $\log(\rho_j)$ by the synthetic instrument we constructed knowing the underlying values of the productivity fundamentals. Model (3) does the same using the radial distance from the geographical centre of the network as an instrument. Finally, Model (4) utilises both instruments to estimate $\log(\rho_j)$ in the first stage of 2SLS method. The standard errors (in parentheses) show that we get significant estimates in all four cases.

The naïve OLS specification clearly overestimates the elasticity which appears more than twice as high as the original value of 0.044. This finding is in accordance with the empirical literature: by ignoring the unobserved determinants of productivity a naïve empirical approach assigns too much importance to agglomeration in explaining TFP. Our main observation is that the IV approach enables us to reduce this bias significantly. In the current sample and data generating

[105] DeBruine, L., Krystalli, A., & Heiss, A. (2021). Faux: Simulation for factorial designs. *R Package Version*, *1*(0).

methodology, the synthetic instrument reduces the estimate to 0.063. The geographical instrument slightly underestimates η with a value slightly less then 0.03. The combination of the two instruments achieves the best result with 0.05 and acceptable statistical significance. However, in light of the previous sections of the report we do not believe that an instrument can in practice separate entirely the productivity gains from time savings from those caused by the agglomeration externality. The present 2SLS example serves as a demonstration of the synthetical data analysis only.

We must emphasise that the simple instrumental variables approach we present here does not eliminate the endogeneity bias entirely. A likely cause of the remaining bias is that M_j and H_j are also highly correlated with the unobserved a_j and thus these covariates are also endogenous. This conclusion underlines the need for more sophisticated empirical approaches, as elaborated earlier in the study, until a synthetic benchmark model like this reproduces the known agglomeration parameter. The simulation is easy to extend to multiple time periods featuring different spatial equilibria in the data generating process. In a panel data setting the inclusion of fixed effects would considerably reduce the bias correction that IVs have to achieve by controlling time-invariant confounding.

5.3 Economic evaluation

In the second application of the benchmark model (i) a hypothetical transport policy will be simulated, (ii) the corresponding spatial equilibrium will be computed, and (iii) the general equilibrium welfare measure will be benchmarked against the partial equilibrium appraisal methodology. Once again, our aim is to present an illustrative application of the benchmarking approach instead of proving far-reaching general conclusions about superiority of any of the competing methodologies.

5.3.1 Simulating a transport improvement

Recall that in the original grid network, moving between any of the neighbouring nodes involves the same 15-minute duration and an expenditure of one monetary unit. In this exercise we simulate a major transport improvement by connecting two arbitrary locations at the city boundaries through more central places. This randomly selected layout is depicted in Panel A of Figure 6. We assume that travel times drop substantially along the highlighted graph edges, from 15 minutes to just 2 minutes. This improvement mimics the introduction of urban mass transit in a highly congested car-oriented city or a walking-oriented historic city. The monetary cost of travel remains unchanged.

With the new travel time matrix, we recalculate the effective density for each location, keeping the distribution of employment unchanged first. This resembles static agglomeration: the fact that the reduction in impedance may act as an effective densification of the urban economy. Panel B of Figure 6 shows the resulting pattern of ATEM. Not surprisingly, the locations directly connected by the transport infrastructure gain the most and this effect is fading away as we move towards more remote places. Note that, by definition, the change in static agglomeration is strictly non-negative in a model in which transport costs decrease while employment remains unchanged.

In the next step we run the general equilibrium model again, allowing workers to relocate and prices and wages to adjust in line with the market clearing conditions. In the new equilibrium, the distribution of workplaces modifies, and thus we get a new pattern of effective densities that we call the dynamic change in agglomeration. In principle, the dynamic change may well be negative as well in certain locations. Panel C reveals this is indeed the case, as the North-Western and South-Eastern dynamic ATEM changes are negative, which highlights the *agglomeration shadow* frequently referred to in the literature.[106]. Panel D compares the two cases but taking the difference between the dynamic and static ATEM adjustments. In a sense this panel shows the expected evolution of ATEM in the process of the spatial reorganisation of economic activity in response to the policy, as we proceed from the very short-run to a long-run equilibrium.

[106] Fujita, M., Krugman, P. R., & Venables, A. (2001). *The spatial economy: Cities, regions, and international trade*. MIT press.

Figure 6: The layout of a hypothetical transport improvement and its impact on static and dynamic changes in access to economic mass (ATEM)

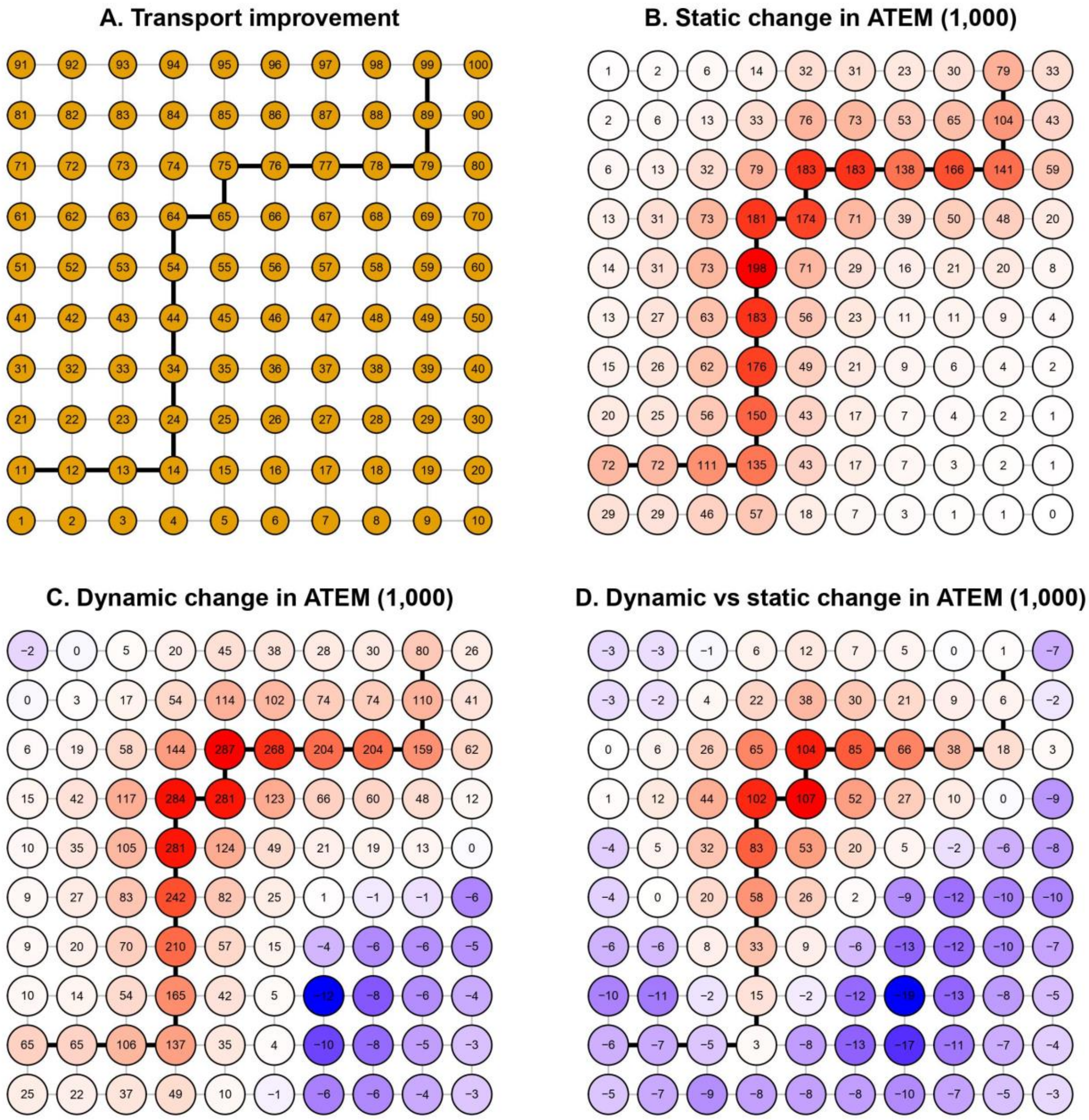
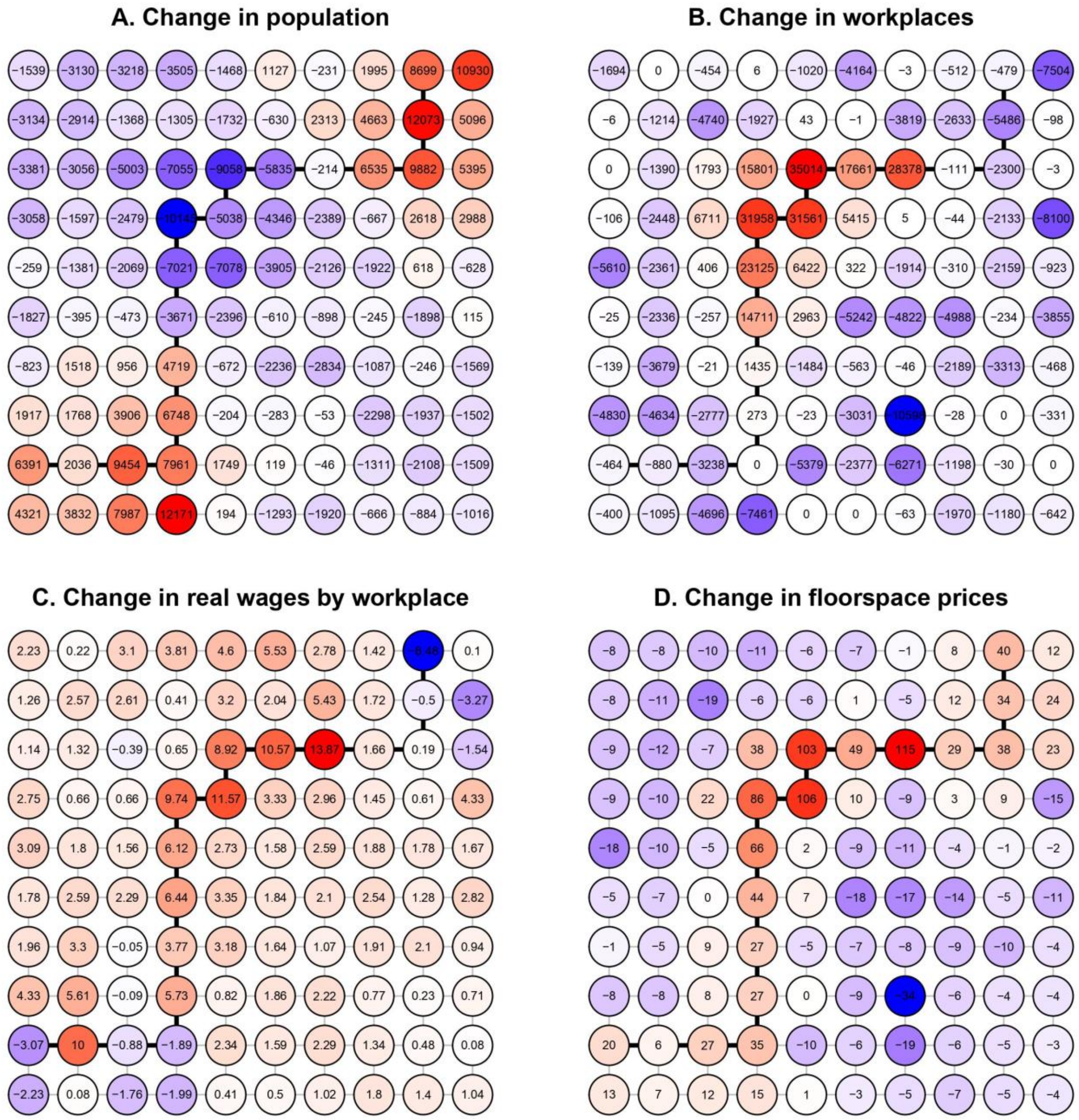


Figure 7 below reveals further insights about the spatial outcomes of the transport policy. Panel A shows a systematic pattern in the relocation of households to the peripheral regions newly connected by the fast transport service. The pattern of suburbanisation is not universal: some of the suburban locations not connected by the new service also lose some population due to the reduction in their connectivity relative to the South-West and the North-East. In terms of the relocation of employment, Figure B shows that the new workplaces are indeed along the new rail line, and the most attractive locations witness a disproportionate increase in workers. These are the places where the fundamental productivity is already high and/or where firms can locate close to the new residential concentrations. These places grow in terms of employment to the expense of a diverse mix of origins throughout the city.

Figure 7: The economic outcomes of the transport improvement in general equilibrium



Panel C shows the change in real wages. This is the income that workers earn at each workplace, bearing in mind that both labour supply and the cost of commuting may change in response to the transport improvement. In the new spatial equilibrium, wages increase almost everywhere in the city, although the increase is mild in the poorly connected areas. Workers' real income increases particularly heavily along the central parts of the transport corridor. By contrast, this measure of the wage decreases by both ends of the line, in line with the reduction in workplaces we observed in panel B. Panel D shows an obvious pattern in terms of floorspace prices: real estate becomes significantly more expensive along the transport corridor while the prices decrease elsewhere.

5.3.2 Alternative welfare measures

We compute the welfare effect of the simulated transport improvement and the resulting reorganisation of economic activity in three ways. Methods 1 and 2 comply with TAG by deriving Direct User Benefits (DUB) and Wider Economic Impacts (WEI) separately while Method 3 uses the SCGE model directly to derive a single welfare measure from the changes in expected household utility and land values.

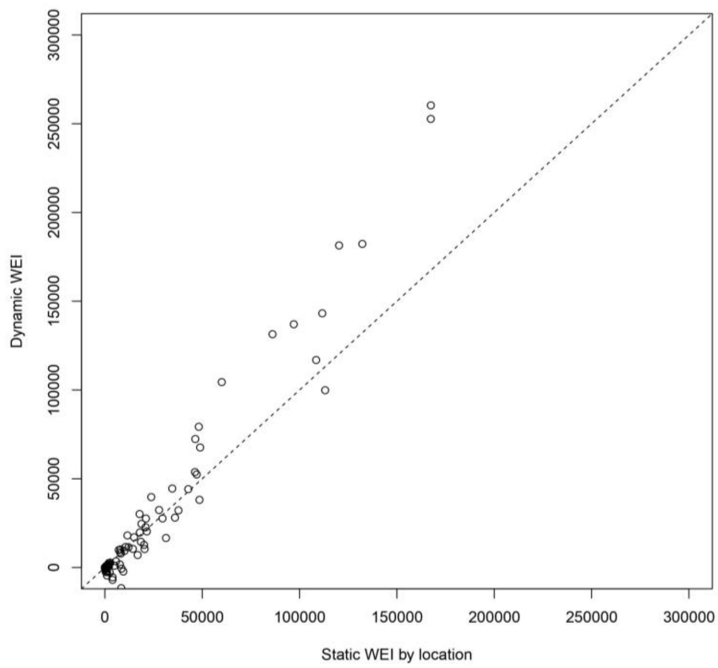
Methods 1 and 2 compute DUBs from travel time savings, and therefore these are heavily reliant on the monetary valuation of time (VOT). This measure is normally estimated in a separate empirical study based on stated or revealed preference data. Existing estimates in the literature are unlikely to comply with the calibration of this toy model. In the SCGE model we selected, however, one can derive an analytical expression for the VOT by calculating the ratio of the marginal utility of time and the marginal utility of money. This theoretical quantity measures the pure opportunity cost of leisure time, excluding other factors such as the inconvenience of travel as an activity.[107] It represents a conservative approximation of empirical values of time.

Our analytical approach produces different time valuations for each OD pair. In principle, this would enable us to keep VOT spatially differentiated in throughout the appraisal exercise. Such differentiation is not applied in TAG for multiple practical reasons. Thus, in this study we also take a representative value by computing the mean VOT weighted by OD-level commuting flows. With this, let us now specify the following appraisal methods.

Method 1: static/short-run PE analysis – First we ignore the spatial reorganisation of economic activity, mimicking a fully static transport model. As in the current model there is no other decision margin through which travel demand might be induced (i.e. commuting is the only trip purpose), DUBs are reduced to the monetised travel time savings of existing commuters with a fixed travel OD-matrix.[108]

WEIs are computed on the basis of the static change in ATEM depicted in Panel B of Figure 3. More specifically, we calculate the relative change in ATEM of each location, apply the agglomeration elasticity of $\eta = 0.044$, and multiply the resulting proportional change in productivity by the baseline economic output Y_j. The latter choice is not trivial. Unit A2.4 of WebTAG prescribes that the predicted change in productivity should be multiplied by GDP per worker and then aggreged over all industries and locations. GDP has no equivalent measure in our microeconomic model.

Figure 8: Static versus dynamic WEIs by location



Method 2: long-run PE analysis – This approach remains in line with TAG but we assume that a gravity-based 4-stage transport model or appropriate long-run demand elasticities are able to

[107] Mackie, P., Jara-Díaz, S., & Fowkes, A. S. (2001). The value of travel time savings in evaluation. *Transportation Research Part E: Logistics and Transportation Review*, *37*(2-3), 91-106.
[108] Note, however, that we allow commuters to reroute after the transport improvement, so in a traditional 4-stage model this short-run scenario is equivalent to muting trip generation and distribution (stages 1 and 2) only.

predict the post-intervention commuting volumes and the dynamic ATEM distribution depicted in Panel C of Figure 6. Due to the presence of induced demand, the DUB calculation must rely on a measure of consumer surplus that we approximate via the Rule of a Half.

The calculation of WEIs remains equivalent to Method 1 except that we consider the dynamic ATEM pattern when we predict productivity gains (and in some cases losses). Figure 8 shows that in the present exercise the location-specific dynamic WEI results do not differ substantially from the static measures, and most of the aggregate difference stems from a handful of locations that serve as employment magnets.

Method 3: SCGE welfare measure – The third metric we benchmark is a welfare measure derived directly from the SCGE model. In this case DUBs and WEIs cannot be differentiated from each other because household utility integrates the benefit of travel time savings with the benefits or relocation to more attractive places, wages, housing prices, etc, in an additively non-separable manner. We follow the approach of Koster[109] by calculating, for the representative household, the compensating income that achieves the same improvement in expected utility that the transport improvement achieves in general equilibrium. This monetary measure of welfare is comparable with other monetary costs and benefits in a CBA.

As the production and floorspace construction sectors are perfectly competitive and absent of externalities in this model, additional welfare gains or losses are not realised in these sectors. However, the amount of land is fixed in the model and its market price increases with demand for floorspace. We add the predicted change in land prices to the SCGE welfare measure.

5.3.3 Numerical results

Table 5 reports the results of the economic evaluation of the simulated transport intervention. The numerical implementation of the model considers daily wages and two commuting trips per effective workday supplied. Therefore, the welfare measures in the table should be interpreted as a daily aggregate social benefit in millions of the monetary unit (price of the numeraire consumption good).

Even though the model has been calibrated arbitrarily, the numerical results are mostly in line with economic intuition. For example, the long-run partial equilibrium welfare (both DUB and WEI) is greater than the short-run estimate. In the partial equilibrium results, WEIs constitute a significant fraction of the total welfare effect but DUBs are still the most voluminous components. More specifically, the short-run WEI is 64% of the DUB while this fraction is 51% in the dynamic case.

The fact that the total welfare effect In the static PE model is nearly identical to the SCGE measure is a remarkable outcome of the simulation which remained surprisingly robust across many simulation runs. This finding confirms that the traditional measure of consumer surplus derived from travel time savings and a reliably quantified time valuation remains a robust approximation of consumer benefits in general equilibrium. We performed additional simulations to check if the minor gap between the short-run partial equilibrium and the SCGE welfare measures (6.15 vs. 6.07) can be attributed to the fact that we used a uniform value of time in the former case. After re-running the simulation with OD-specific values of time we get a 6.6% lower welfare result in partial equilibrium, which is lower than the SCGE result. Thus, we reject this hypothesis.

Note that a partial equilibrium calculation in which DUBs are derived from the long-run rearrangement of travel demand and the dynamic change in agglomeration economies (column 2 in Table 2), the welfare result is significantly higher, 8.67 as opposed to 6.15. If, in a practical appraisal exercise, the demand model captured a part of these land-use changes without the associated wage and housing price deviations (see e.g. a LUTI model), then the resulting DUB would likely fall between 3.75 and 5.75.

As we already noted in the introduction of this section, the SCGE model is by no means a proven representation of reality. Thus, this result alone does not imply that the short-run PE model gives

[109] Koster, H. R. (2024). The Welfare Effects of Greenbelt Policy: Evidence from England. *The Economic Journal*, *134*(657), 363-401.

correct results while the long-run version does not. This preliminary and illustrative analysis did not involve a deeper investigation of the actual sources of a potential double counting in the long-run approach.

It is also important to note that direct user benefits are less than the SCGE welfare result, even in the dynamic model in which we assume a perfect traffic forecast that includes the travel demand induced by relocation. Once again, this is a preliminary and illustrative result which is consistent with the widely held view that adding some sort of wider economic impacts to direct user benefits might be justifiable, supporting the UK state-of the-practice in transport appraisal.

Table 5: Aggregate welfare effect of the transport policy in monetary units (in millions)

	TAG methodology		SCGE
	Short-run predictions	Long-run predictions	
Direct User Benefits	3.75	5.75	-
Wider Economic Impacts	2.41	2.93	-
Total	6.15	8.67	6.07

5.4 Future extensions

The SCGE model tested in this section serves demonstrational purposes and it can be extended in many ways to provide supplementary evidence for the estimation of agglomeration economies. Such extensions would be in line with the additional features that the analyst intends to implement in the TAG framework and the estimation of the underlying elasticities.

One obvious limitation of the current model is that transport is represented in a stylised way: only one mode of transport is considered and route choice is also deterministic. A more advanced realisation of the mode should incorporate congestion, i.e. a feedback effect through which higher transport flows increase the user cost of travelling. Another important aim of future extensions might be to capture non-work travel and the fact that a significant part of the travel demand induced by transport interventions do not contribute to firm productivity in the urban economy.

There is room to consider other types of agglomeration mechanisms in this framework. The distribution of the fundamental residential and workplace amenity levels, X_i and E_j, remain exogenous in the present implementation. These variables might depend on a range of spatial outcomes such as the surrounding economic density in an ATEM fashion,[110] the proximity of natural resources,[111] or the intensity of motorised traffic flows and the amount of urban space allocated to such uses, which have not been explored in the literature so far. The obvious challenge is that such amenity externalities are difficult to capture in the partial equilibrium framework of TAG.

The current version of the SCGE model assumes perfect competition and costless trade in the urban economy. As Anas and Liu,[112] Monte et al.[113] and a series of follow-up SCGE models demonstrate, adding imperfect competition in the form of a Dixit–Stiglitz-type specification is feasible in this framework. Monopolistic competition enables the analyst to measure consumption externalities stemming from scale economies and spatial competition.

[110] Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., & Wolf, N. (2015). The economics of density: Evidence from the Berlin Wall. Econometrica, 83(6), 2127-2189.

[111] Koster, H. R. (2024). The welfare effects of greenbelt policy: Evidence from England. The Economic Journal, 134(657), 363-401.

[112] Anas, A., & Liu, Y. (2007). A regional economy, land use, and transportation model (RELU-TRAN©): formulation, algorithm design, and testing. Journal of regional science, 47(3), 415-455.

[113] Monte, F., Redding, S. J., & Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, *108*(12), 3855-3890.

Finally, one may consider the implementation of an SCGE benchmark model with exactly the same spatial layout where the appraisal exercise is about to take place. In such cases it becomes a Supplementary Economic Model (SEM) instead of a benchmark model with the sole aim of testing the methodologies applied in appraisal.

Conclusions

- The section demonstrated that a tailor-made SCGE model is suitable to mimic the data generating process of the empirical analyses of agglomeration economies. This synthetic data is randomly generated but the relationship between its variables remains consistent with spatial economic theory.
- The synthetic data is suitable to test empirical techniques aimed at eliminating the endogeneity bias caused by omitted variable bias, for example. In an illustrative example we remove a location-specific determinant of firm productivity correlated with agglomeration and show that even the simplest cross-sectional instrumental variables estimation is suitable to remove a significant part of the endogeneity bias.
- Our benchmark SCGE model produces an integrated (theoretically consistent) welfare estimate for any hypothetical transport improvement in the model network. This evaluation metric is then compared with the common partial equilibrium CBA method outlined in TAG. This benchmarking exercise confirms that the sum of short-run direct user benefits and static wider economic impacts is consistent with the general equilibrium welfare estimate, thus hinting that double counting is avoided in the baseline TAG methodology.

6. COVID-19 and agglomeration

This section provides an overview of the drivers of change through which the COVID-19 pandemic has affected the mechanisms underpinning agglomeration economies, and explores the wider implications that such change could have on agglomeration spillovers and their measurement.

6.1 Drivers of change

Working location

The pandemic has impacted the way we work together, leading to the rise of working from home (WFH) in several countries across the globe. In the UK, a trend existed even before the pandemic, as indicated by the ONS Labour Force Survey (LFS) with the share of homeworkers set at 14.5% in 2019[114] that more than doubled by January to March 2022 to over 30%.[115] Importantly, the propensity to WFH would vary across industries both before and after the breakout of COVID-19 (greater in professional services and information and communication) as well as occupations (with lowest propensity to only travel to work for managers and senior officials and highest for elementary occupations)[116].

Travel behaviour

Alongside changing working locations, the pandemic has brought about a shift in travel behaviour affecting elements such as travel mode, frequency, and purpose. In the UK, survey data from November 2022[117] indicates a significant reduction in the number of people reporting to use public transport at least monthly compared to pre-pandemic levels (although increasing since November 2021), and a rise in people adopting informal car-pooling. Nonetheless, the share of respondents reporting a *frequent* usage of public transport (i.e., at least weekly) has significantly increased, especially for trains (from 14 in January-March 2020 to 21% in November 2022) and metro (13 to 18%). The average number of reasons for travelling has also decreased, mirrored by a fall in the share of respondents reporting to travel for several recreational purposes including cultural activities, eating out, and visiting people – on top of lower commuting to work and visiting medical facilities.

Consumer behaviour

Finally, COVID-19 has also caused sustained change in the frequency, location, and way of purchasing goods and services. In the UK, after a first surge in online sales out of sales during the pandemic and a subsequent decrease, the share out of total retail sales (excluding automotive fuel) has remained stable since March 2022 on average (26.4% until February 2024), a change of over 7% compared to the March 2018-February 2020 average[118]. Moreover, since the pandemic, consumers have maintained a tendency to shop more locally and frequently compared to pre-pandemic levels[119]. Furthermore, the combined higher vacancy rates of retail and leisure units in high streets and lower rates in retail parks compared to pre-pandemic levels indicate a shift from centres to peripheries in shopping behaviour[120].

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[114] Office for National Statistics (2020). Coronavirus and WFH in the UK labour market: 2019.
[115] Office for National Statistics (2022). Homeworking in the UK – regional patterns.
[116] Office for National Statistics (2021). Business and individual attitudes towards the future of homeworking, UK: April to May 2021, and *idem* (2023). Characteristics of homeworkers, Great Britain: September 2022 to January 2023 and source in footnote 114.
[117] Ipsos for the Department for Transport (2023). Our Changing Travel. Research into how people's travel choices are changing, November 2022.
[118] Office for National Statistics (March 2024). Retail Sales Index internet sales.
[119] See Ward, M. (2024). Retail sector in the UK. House of Commons Library Briefing Paper.
[120] Ibidem. See also Garton Grimwood, G. et al, (2021). Town centre regeneration. House of Commons Library Briefing Paper.

6.2 Wider impacts and consequences for appraisal

The combination of the drivers of changes set out in the previous section can result in a number of different scenarios, affecting agglomeration spillovers of transport interventions via the channels of resource matching, sharing, and knowledge diffusion[121]. WFH could improve baseline workforce matching, as the pool of workers that a firm could employ might be located further away compared to pre-pandemic levels. As a result, the change between with-scheme and without-scheme workforce matching, may lead to lower agglomeration benefits than those identified at scheme appraisal.

Baseline knowledge creation and diffusion could instead worsen, resulting in improved agglomeration spillovers from a transport intervention. Indeed, evidence suggests that information sharing benefits arise more likely in environments that facilitate meeting spontaneously and in person[122]. The misalignment between employees and employers' preferences for WFH – higher for the former[123] – might also result in a below-optimal level of remote working for the firm's productivity when employees perform better in an office[124]. In this case, a transport intervention facilitating commuting might improve firms' productivity, although evidence of WFH impacts on individual performance is mixed - ranging from an increase in work intensity and psychological fatigue (in the UK) to greater work-life balance, better quality of life, and enhanced productivity[125].

The changing travel and consumer behaviour could instead affect land-use choices in terms of where people decide to live, firms decide to establish their offices, and businesses decide to trade, altering pre-pandemic mechanisms of sharing of resources. Urban transformation might realise at a different pace in different geographies, depending on local contexts and market dynamics, as the search for larger dwellings in cities outskirts could be inhibited by factors such as an inelastic housing supply or reduced purchasing power of consumers. For example, the USA have witnessed the advent of the 'donut effect', whereby demand for housing has surged in the peripheries to the detriment of city centres[126]; however, a similar effect has not yet been univocally observed in the UK. Here, 2021 analysis has shown that a 'halo effect' could be measured across cities (10% house price rise in less dense areas against 6% in more populous areas), but this was mostly driven by a small segment of wealthier households[127]. A separate OECD study examining COVID-19 impact on the geography of housing demand corroborates the different trend that the UK has seemingly underwent compared to other geographies. Unlike most of the cities analysed for Germany, Spain, France, and Portugal, the growth rate in sqm house prices between 2019 and 2021 has remained higher in city cores compared to that of commuting or more peripheral

[121] See breakdown in Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In Handbook of regional and urban economics (Vol. 4, pp. 2063-2117). Elsevier.

[122] Rosenthal, S. S., & Strange, W. C. (2020). How close is close? The spatial reach of agglomeration economies. Journal of Economic Perspectives, 34, 27-49.

[123] Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2022). Working from home around the world (No. w30446). National Bureau of Economic Research

[124] Behrens, K., Kichko, S., & Thisse, J. F. (2021). Working from home: Too much of a good thing?. Available at SSRN 3768910.

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zones[128]. Social-Network meta-data has also indicated that a movement from city centres to peripheries or urban areas might have been temporary in Britain[129].

Overall, estimates of parameters underpinning the appraisal of transport agglomeration impacts would require updating to reflect the socioeconomic changes brought about by COVID-19. However, recent and emerging research indicates that a post-pandemic equilibrium might have not been yet reached – with researchers making use of forecasting models to predict urban change rather than look backwards[130]. In line with the recommendations from Laird & Tveter (2021) for the Department for Transport, scenario analysis and sensitivities should be adopted during appraisal to account for uncertainty in the long-term impacts of COVID-19 on productivity and land-use change. Subsequent research has provided indications on potential sensitivities to undertake, stressing how the separation of agglomeration impacts by sharing, matching, and knowledge spillover channels would be ideal for enhanced appraisal outcomes, but hard to realise in practice[131]. Section 4.1 provided more detailed recommendations on challenges of separately identifying these channels in an empirical framework.

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7. Conclusions

This technical report sets out the scope of a study aimed at large-scale re-estimation of the agglomeration parameters applied in the Department for Transport (DfT) Transport Analysis Guidance (TAG), wherein agglomeration impacts for transport schemes are appraised within Cost Benefit Analysis (CBA). The report reviews the developments in the literature on agglomeration and transport appraisal, specifically, in relation to some key themes identified by the DfT. The underlying aim is to assess whether and how they can be incorporated in the scope of the re-estimation study. A condensed list of these themes is provided below.

a) Eliminating overlap between the wider economic impacts (WEIs) of agglomeration and the other categories of impacts assessed in the TAG methodology.

b) Distinguishing the two main types of agglomeration economies in calculations: urbanisation economies and localisation economies.

c) Appraising amenity and consumption externalities and wider relocation costs within TAG.

d) Disentangling contributions from the micro-mechanisms of agglomeration: sharing, matching and learning

e) Identifying appropriate access to economic mass measures of agglomeration for modelling ‘real’ versus ‘effective’ density benefits.

f) Understanding the spatial scope of agglomeration economies in terms of distance-decay and addressing concerns related to the modifiable arial unit problem.

g) Accounting for non-linearities and endogeneity biases in empirical estimation.

h) Quantifying heterogeneity in agglomeration parameters, for instance, by area type and mode of travel.

Following from the review, the report provides recommendations for theoretical and empirical work to be conducted as part of the aforementioned re-estimation exercise.

The main findings of this report with respect to each of these themes are summarised below.

Overlap of direct and wider impacts

- The evaluation of impacts in CBA adheres to the principle of additionality, which requires distinct impacts and groups of impacts considered in the assessment to be non-overlapping. This fundamental principle forms the basis of the DfT TAG method for appraisal.
- Overlap between TAG Level 1 direct welfare effects and TAG Level 2 wider economic impacts of agglomeration can arise due to the influence of time-dependent productivity effects arising from reduction in generalised travel costs (GTCs).
- The use of a distance-based ATEM measure removes variance in GTCs when estimating the agglomeration elasticity, thereby reducing potential for direct capture of travel time productivity effects in the elasticity. Nevertheless, the simultaneous existence of externality and non-externality effects on productivity which scale with ATEM makes it challenging to empirically distinguish the two effects due to observational equivalence. Therefore, distance-based elasticities of productivity with respect to ATEM do not necessarily guarantee identification of a pure agglomeration externality effect.
- By design, the GTC-based ATEM measure captures spatiotemporal variances in travel times and costs. Therefore, without a change in the fundamental approach used to calculate WEIs of agglomeration, the use of GTC based elasticities will definitively result in double counting because econometric estimation of GTC elasticities cannot isolate productivity effects of agglomeration from DUBs generated from time savings.
- It is also important to net out dynamic (Level 3) WEIs of agglomeration arising due to spatial sorting and relocation of firms and workers by productivity from static (Level 2) WEIs. In wage models, this can be achieved via a combination of direct covariate

adjustment and use of worker-specific fixed effects. In TFP models, these can be adjusted by adopting an estimation based on instrumental variables (IV) or control function (CF).

- With respect to reformulating the econometric model of agglomeration, a zone-level productivity model that estimates both the productivity effects resulting from cost savings (DUBs) and from changes in effective density (agglomeration externalities) within the same regression is certainly appealing and worthy of further investigation. However, because zones are not the primary units of production, rather the firms within are, the implicit choice of boundaries in zonal models requires attention.
- As the most severe double-counting threat arises from firms being transport users themselves, it is worth exploring the addition of transport explicitly as a factor of production, in addition to labour, material, capital and externalities. This approach could allow separating the productivity effects that result from firms' direct use of transport from those due to the externality.

Distinction between urbanisation and localisation economies

- In theory, urbanisation and localisation effects can be separately represented using urbanisation and localisation ATEM variables and estimating the two elasticities within the same econometric model.
- However, in practice, it is difficult to disentangle the two effects because not only are the two variables highly collinear, but they also have the same effect on productivity, leading to a problem of equivalence of outcomes.
- Moreover, from Duranton and Puga (2004), it is known that the urbanisation and localisation share the same origins and outcomes. Therefore, it is also worth exploring whether the distinction between the two effects is theoretically well-founded.
- Further, as Graham and Gibbons (2019) highlight, any transport intervention is unlikely to alter localisation without simultaneously altering urbanisation or vice-versa. Thus, viewing these two effects as independent additive components rather than integrating them into a broader agglomeration term may not offer any significant additional insights.

Amenity and consumption externalities and wider relocation costs

- A small but growing number of studies provide empirical evidence on the existence of a link between access to economic mass and consumption/amenity benefits (and costs) in an urban environment. Such benefits may emerge through variety in non-tradable services in accessible locations, public goods unlocked by a dense built environment, the high frequency of human interaction, and potential nuisance factors associated with density.
- At the same time, empirical evidence on the amenity effect of transport improvements specifically is scarce in the same literature.
- Two prototype studies show that both consumption and amenity externalities can be encapsulated in general equilibrium models such that this channel is included in the calculation of the welfare effect of a transport policy. However, these general equilibrium effects are not directly compatible with TAG.
- Fundamental research needs to be performed to prove that consumption and amenity externalities can be quantified in the partial equilibrium appraisal method of TAG without double counting.
- Spatial general equilibrium models can deliver elasticities of amenity value with respect to access to economic mass. However, the contribution of amenity spillovers to welfare is not additively separable. Therefore, application of these elasticities in partial equilibrium framework of TAG may lead to double counting of impacts.

Contributions from the micro-mechanisms of agglomeration

- Theory distinguishes the benefits of agglomeration resulting from the three key micro-mechanisms: sharing, matching, and learning, whereas, in practice, the three mechanisms are likely to act together and have the same general effect on productivity (for instance, creating gains). So, there may not be enough variation in the data to disentangle the effects, which again leads to the issue of equivalence of outcomes.

- Most previous studies in this area are, therefore, limited to identifying the existence of the sources of agglomeration, rather than linking these sources to productivity.
- To isolate the contributions from various sources of agglomeration, one may consider exploring natural experiments where there is enough variation in the contributions with one of the forces are in play and others are not. However, it is worth emphasising that it is hard to identify such situations in practice.

Real versus effective density driven benefits and impedance measures

- As there is no definitive metric for agglomeration, access to economic mass (ATEM) serves as a proxy to depict it. TAG recommends the use of effective density (ED) as a measure of ATEM, which characterises the market potential of a particular area. The ED proxy combines a representation of the spatial distribution of economic mass and an impedance function signifying the difficulty in accessing the economic mass.
- Potential measures of economic mass commonly include GVA, employment and population, but can also include a combination of these.
- The current TAG calculation of agglomeration externalities employs a Euclidean distance-based measure to represent impedance in the ATEM. The intuition is to remove variance in travel costs when estimating the agglomeration elasticity, thereby reducing potential for direct capture of travel time productivity effects in the elasticity.
- Yet, the use of GTC-based impedance is more appealing to practitioners for two key reasons: (a) Adopting GTC-based ATEM makes outputs from transport models consistent with inputs to the econometric model of agglomeration, and (b) GTC-based ATEM can be calculated for different modes and can vary by time of the day, thereby taking into account network conditions and therefore more accurately representing the impedance in access to economic mass.
- While by changing in the fundamental approach to calculate agglomeration externalities, GTC-based ATEM can validly be used in appraisal, it is worth noting that the measure is limited in its ability to capture the ‘real’ density-driven benefits of agglomeration. For instance, there may be scenarios where transport improvements may generate changes in traffic volumes without affecting the GTCs. Under such scenarios, the GTC-based ATEM will fail to capture the increase in market size and, consequently, the associated productivity gains.
- A potential solution to capture the real density-driven benefits of transport improvements is to use actual travel flows (that is, observed number of trips) in calculations. Potential ATEM measures that combine observed flows and Euclidean distances are worthy of future investigation.

Functional form of decay parameters

- Agglomeration indices constructed for empirical analysis should reflect the potential benefits that an economic agent can gain from agglomeration mechanisms in its locality, while also distinctly defining the concept of 'locality'.
- Accordingly, the level of agglomeration experienced by a given agent is generally defined by aggregating economic mass in the geographical neighbourhood of the agent with higher weights applied to locations close to the agent, and lower weights to those further away.
- To represent the importance of proximity and the spatial scope of agglomeration, TAG currently uses an exponent on the chosen measure of impedance (Euclidean distance) within the ED index. This exponent is commonly known as the distance decay parameter. The advantage of this approach lies in the fact that it necessitates the estimation and insertion of only one parameter into appraisal calculations.

- More flexible approaches to represent this phenomenon include the piecemeal distance (or cost) band method or modelling of distance (or cost) decay via semi-parametric regression.

The level of spatial aggregation

- For empirical estimation of the agglomeration model, micro data on economic agents are aggregated into discrete spatial units, commonly referred to as zones. In most practical applications, the zoning system adopted for calculations is consistent with pre-defined administrative boundaries.
- Nonetheless, a series of studies have shown that the chosen unit of aggregation has important implications for statistical inference. This issue is commonly recognised in the literature as the Modifiable Areal Unit Problem (MAUP).
- While a recent study suggests calculating agglomeration benefits at the lowest possible level of aggregation to minimise MAUP concerns, another key study on this theme demonstrates that MAUP concerns are only severe when no adjustments for confounding are made in estimation of the agglomeration model.

Endogeneity issues, empirical estimation, and their validation

- Confounding factors such as unobserved firm-level sources of productivity that concurrently impact both agglomeration and productivity and other sources endogeneity such as reverse causality can obstruct the determination of a causal linkage within the analysed economic data.
- It is, therefore, important to adjust for potential biases from endogeneity in estimation of the econometric model of agglomeration.
- Consistency of panel individual effects, within or first-differenced estimation commonly employed in calculations requires the absence of time-variant confounding, which is potentially unrealistic in most empirical settings.
- Panel IV and Panel CF approaches provide a more well-rounded means to address biases from time-invariant and time-varying confounding and other sources of endogeneity such as reverse causality. The former approach requires valid IVs (strong correlated with agglomeration but purely exogenous to productivity) for identification, while the latter approach requires theoretical assumptions on firm behaviour to hold.

Non-linearities in functional forms

- Most existing studies pre-specify the agglomeration-productivity relationship using a log-linear functional form, which implies a concave and non-decreasing function in levels.
- Nevertheless, this functional form approximation seems inconsistent with economic theory that predicts the marginal returns to agglomeration to decrease with city size, for instance, due to higher congestion and land costs in denser cities.
- It has, in fact, been pointed out that the agglomeration-productivity relationship should be concave and bell-shaped curve, owing to the interplay between the costs and benefits of agglomeration. This implies that effect of city scale can be heterogeneous across ranges of agglomeration, with positive and negative gradients, thresholds, and flat regions across the range. Interestingly, there is now some empirical evidence in the literature that confirms such hypotheses.
- Consequently, it is important that the agglomeration model is flexible enough to capture the presence of non-linearities of agglomeration effects. Two step approaches; where total factor productivity (TFP) is obtained from the production function in a first stage model, and the predicted values of TFP then regressed on agglomeration and other spatial variables in a second stage regression; allow for more flexibility in modelling the agglomeration-productivity relationship, including application of non-parametric or semi-parametric causal methods.

Heterogeneity in parameters

- It is possible to allow for heterogeneous responses of productivity to agglomeration within the econometric model, thus yielding potentially different elasticities for different sub-groups.
- The most straightforward approach to achieve this objective is to calculate separate agglomeration elasticities for relevant sub-samples of the data. Another possible approach involves interacting the adopted ATEM measure with category-specific dummy variables to quantify heterogeneity by relevant categories.
- Estimation of distinct agglomeration elasticities by industry type is popular in the literature but exploring heterogeneity in the responsiveness of productivity to agglomeration by area type, by functional characteristics of firms, and by trip purpose are also worth exploring.

Differential elasticities by mode and the role of active travel

- In theory, the current TAG calculations can be extended to include mode-specific agglomeration effects. However, mode-specific EDs constructed using identical mass measures for each mode tend to be highly correlated, thereby leading to issues of severe multicollinearity when estimating multiple mode-specific elasticities in a single regression model.
- Moreover, the economic benefits of agglomeration for firms and workers hinge more on the overall accessibility of their location than on individual transport modes, making the assessment of how various transport modes enhance accessibility more relevant than quantifying their specific contributions.

A.1 Technical Appendix

This appendix details the technical specificities of the benchmark SCGE model covered in Section 5. The structure of the model is depicted schematically in Figure 2 of the report. The discussion below follows the figure by first defining household behaviour and then the production and floorspace construction sectors.

Glossary of notations

C_{ij}	goods consumption (a composite)
H_{ij}^{R}	residential floorspace consumption
H_{j}^{W}	commercial floorspace use
q_i	price of (residential) floorspace
q_j^W	price of commercial floorspace; $q_i^W = \xi q_i$
p_i	consumption price
L_{ij}	leisure time
$\bar{L}$	time endowment; normalise $\bar{L} = 1$
T	fixed length of a workday $T < 1$
τ_{ij}	monetary price of travel
t_{ij}	travel time
v_{ij}	marginal value of time
x_{ij}	individual labour supply
z_{ij}	Fréchet-distributed idiosyncratic component of household utility
ϵ	shape parameter of the Fréchet distribution of z_{ij}
λ_{ij}	location choice probabilities
Y_j	output of representative firm in location j
A_j	productivity
η	elasticity of firm productivity with respect to agglomeration
δ	distance decay parameter of agglomeration
N_i^R	residential population
N_j^W	workplace population
k_i	final goods used as input of floorspace construction
Λ_i	land endowment
l_i	land input of floorspace construction
ℓ_{i}	price of land
$\bar{H}_i$	density limit due to zoning and other similar regulation

Household behaviour

Household utility function (Cobb-Douglas)

$$U_{ij} = \left(\frac{L_{ij}}{1-\gamma}\right)^{1-\gamma} \left(\frac{K_{ij}}{\gamma}\right)^{\gamma} z_{ij}$$

Sub-utility for consumption (Cobb-Douglas

$$K_{ij} = \left(\frac{C_{ij}}{\beta}\right)^{\beta} \left(\frac{H_{ij}^R}{1-\beta}\right)^{1-\beta}$$

Monetary budget constraint

$$x_{ij}\left(w_j - \tau_{ij}\right) = p_i C_{ij} + q_i H_{ij}^R$$

Temporal budget constraint

$$\bar{L} = L_{ij} + x_{ij}\left(T + t_{ij}\right)$$

Note that this relationship implies that individual labour supply x_{ij} and travel time t_{ij} directly determine leisure time L_{ij}.

Lagrangian of the household problem

$$\mathcal{L} = U_{ij} - \kappa\left[p_i C_{ij} + q_i H_{ij}^R + x_{ij}\tau_{ij} - x_{ij} w_j\right] - \mu\left[L_{ij} + x_{ij}(T_j + t_{ij}) - \bar{L}\right]$$

Value of time defined as the ratio of the marginal utility of time and money

$$\frac{\partial \mathcal{L}}{\partial x_{ij}} = -\kappa\left(\tau_{ij} - w_j\right) - \mu\left(T_j + t_{ij}\right) = 0 \rightarrow v_{ij} = \frac{\mu}{\kappa} = \frac{w_j - \tau_{ij}}{T_j + t_{ij}}$$

Solutions of the household problem – Optimal leisure time

$$L_{ij} = (1-\gamma)\bar{L}$$

Optimal consumption

$$C_{ij} = \beta\gamma \; \frac{v_{ij}\bar{L}}{p_i}$$

Optimal residential floorspace use

$$H_{ij}^R = (1-\beta)\gamma \; \frac{v_{ij}\bar{L}}{q_i}$$

Optimal household labour supply

$$x_{ij} = \frac{\gamma\bar{L}}{T_j + t_{ij}}$$

Indirect sub-utility of the consumption bundle

$$K_{ij} = \gamma\bar{L} \; \frac{v_{ij}}{p_i^{\beta}\, q_i^{1-\beta}}$$

Indirect utility (utility with optimal consumption volumes)

$$u_{ij} = \bar{L}\left(\frac{v_{ij}}{p_i^{\beta}\, q_i^{1-\beta}}\right)^{\gamma} z_{ij}$$

Commuter gravity equations

Specification of idiosyncratic utility z_{ij}: density function of the Frechet distribution

$$F(z_{ij}) = \exp(-X_i E_j \cdot z_{ij}^{-\epsilon})$$

With this distribution of the idiosyncratic part of utility, the probability that residence-workplace pair ij provides the highest level of utility is the following.

$$\lambda_{ij} = \frac{X_i E_j \left(\frac{v_{ij}}{p_i^{\beta}\ q_i^{1-\beta}}\right)^{\gamma\epsilon}}{\sum_r \sum_s \ X_i E_j \left(\frac{v_{rs}}{p_r^{\beta}\ q_r^{1-\beta}}\right)^{\gamma\epsilon}}$$

Choice probability for residential location i alone

$$\lambda_i^R = \sum_j \lambda_{ij} = \frac{\sum_j X_i E_j \left(v_{ij}\right)^{\gamma\epsilon} \ \left(q_i^{1-\beta}\right)^{-\gamma\epsilon}}{\sum_r \sum_s X_r E_s \left(v_{rs}\right)^{\gamma\epsilon} \ \left(q_r^{1-\beta}\right)^{-\gamma\epsilon}}$$

Conditional workplace choice probability

$$\lambda_{ij|i} = \frac{\lambda_{ij}}{\lambda_i^R} = \frac{E_j \ v_{ij}^{\gamma\epsilon}}{\sum_s E_s \ v_{is}^{\gamma\epsilon}}$$

Expected (indirect) utility considering all available residence-workplace alternatives

$$E[u] = \Gamma\left(\frac{\epsilon - 1}{\epsilon}\right)\left[\sum_i \sum_j X_i E_j \left(\frac{v_{ij}}{p_i^{\beta}\ q_i^{1-\beta}}\right)^{\gamma\epsilon}\right]^{1/\epsilon}$$

Goods production

Note that due to endogenous individual labour supply, workplace population and total labour supply are not identical. We introduce mean labour supply per work and total labour supply as follows.

$$\bar{x}_j = \frac{1}{N_j^W} \sum_i N_i x_{ij}$$

$$M_j = \sum_i N_i x_{ij} = N_j^W \bar{x}_j$$

Furthermore, to simplify notation, we avoid subscript j in this sub-section of the Technical Appendix.

Production function (Cobb-Douglas)

$$Y = AM^{\alpha} H^{1-\alpha}$$

Lagrangian of cost minimisation subject to production function

$$\mathcal{L} = wM + qH - \lambda[Y - AM^{\alpha} H^{1-\alpha}]$$

Solutions: optimal factor demand levels

$$M = \left(\frac{1-\alpha}{\alpha}\frac{w}{q}\right)^{\alpha-1} \cdot \frac{Y}{A}$$

$$H_j^W = \left(\frac{1-\alpha}{\alpha}\frac{w}{q}\right)^{\alpha} \cdot \frac{Y}{A}$$

Cost function

$$C(Y_j) = w^{\alpha}\, q^{1-\alpha} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha} \left(\frac{1}{1-\alpha}\right) \frac{Y}{A}$$

Assumption 1: Profit maximisation in the production sector. This implies that $MR(Y_j) = MC(Y_j)$ in this setup, where marginal revenue is p_j that we use as the numeraire of the model, so that $p_j = 1$.

$$1 = w^{\alpha}\, q^{1-\alpha} \left(\frac{1-\alpha}{\alpha}\right)^{\alpha} \left(\frac{1}{1-\alpha}\right) \frac{1}{A}$$

This leads to new expressions for the profit maximising factor demands.

$$M = \left(\frac{\alpha A}{w}\right)^{\frac{1}{1-\alpha}} H$$

$$H = \left(\frac{(1-\alpha)A}{q}\right)^{1/\alpha} M$$

Assumption 2: Perfect competition in the production sector. This implies a zero profit condition under free entry and constant returns to scale.

$$AM^{\alpha}H^{1-\alpha} - wM - qH = 0$$

After substituting M above and rearranging for floorspace price q, we express the zero-profit market-clearing condition for the floorspace price.

$$q = (1-\alpha)A^{1/(1-\alpha)} \left(\frac{\alpha}{w}\right)^{\frac{\alpha}{1-\alpha}}$$

Market-clearing wage

$$w = \alpha A^{1/\alpha} \left(\frac{1-\alpha}{q}\right)^{(1-\alpha)/\alpha}$$

Floorspace construction

Production function (Cobb-Douglas)

$$H_i = Z_i^{1-\psi} (\phi_i(H_i)\, l_i)^{\psi}$$

The stringency of floorspace is captured by $\phi_i(H_i)$.

$$\phi_i(H_i) = \left(1 - \frac{H_i}{\overline{\overline{H}}_i}\right)$$

Lagrangian of cost minimisation subject to production function, assuming that the price of capital is one.

$$\mathcal{L} = Z_i - \ell_i l_i - \lambda \left[H_i - Z_i^{1-\psi} \phi_i^{\psi}\, L_i^{\psi}\right]$$

Optimal land and capital inputs

$$l = H \left(\frac{1-\psi}{\psi}\right)^{\psi-1} \ell^{\psi-1}\, \phi^{-\psi}$$

$$Z = H \left(\frac{1-\psi}{\psi}\right)^{\psi} \ell^{\psi}\, \phi^{-\psi}$$

Cost function

$$C(H) = H\ell^{\psi}\ \phi^{-\psi}(1-\psi)^{-1}\left(\frac{1-\psi}{\psi}\right)^{\psi}$$

Profit maximisation, when $\bar{q}$ denotes the average floorspace price considering the ratio of residential and commercial floorspace use locally.

$$\bar{q} = MC(H)$$

$$\bar{q} = q_i\left(\frac{H_i^R}{H_i} + \frac{H_i^W}{H_i}\xi_i\right)$$

Substitute $C(H)$ above

$$\bar{q} = \left(\psi\frac{\bar{q}H}{\Lambda}\right)^{\psi}\ \phi^{-\psi}(1-\psi)^{-1}\left(\frac{1-\psi}{\psi}\right)^{\psi}$$

Equilibrium residential floorspace price

$$q_i = \frac{1}{1-\psi}\ \left[\left(\frac{1}{H} - \frac{1}{\overline{\overline{H}}}\right)l\right]^{\psi/(\psi-1)}\left(\frac{H_i^R}{H_i} + \frac{H_i^W}{H_i}\xi_i\right)^{-1}$$

Profit maximising floorspace production under zero profit constraint

$$H = \frac{[(1-\psi)\bar{q}]^{\frac{1-\psi}{\psi}}\ l}{1 + [(1-\psi)\bar{q}]^{\frac{1-\psi}{\psi}}\dfrac{l}{\overline{\overline{H}}}}$$

Equilibrium price of land: zero profit in floorspace construction implies that land price is the ψ fraction of total revenue from floorspace sales $\bar{q}_i H_i$ divided by land area.

$$\ell_i = \frac{\psi\ \bar{q}_i H_i}{\Lambda_i}$$

Using the definition of weighted average floorspace price:

$$\ell_i = \psi\ \left(q_i H_i^R + q_i \xi_i H_i^W\right)\Lambda_i^{-1}$$

Spatial equilibrium

Endogenous variables

Residential and workplace populations	N_i^R, N_j^W
Wages	w_j
Residential and commercial floorspace price	q_i, q_j^W
Local productivities	A_j

Equilibrium conditions

The sequence of equilibrium conditions computed and updated in each step of the iterative process of inferring spatial equilibrium.

1) Unconditional location choice probability

$$\lambda_{ij} = \frac{X_i E_j\left(\dfrac{v_{ij}}{p_i^{\beta}\ q_i^{1-\beta}}\right)^{\gamma\epsilon}}{\sum_r \sum_s\ X_r E_s\left(\dfrac{v_{rs}}{p_r^{\beta}\ q_r^{1-\beta}}\right)^{\gamma\epsilon}}$$

2) Conditional workplace choice probability

$$\lambda_{ij|i} = \frac{E_j\, \upsilon_{ij}^{\gamma\epsilon}}{\sum_s E_s\, \upsilon_{is}^{\gamma\epsilon}}$$

3) Residential population

$$N_i^R = N \sum_j \lambda_{ij}$$

3) Workplace population

$$N_j^W = N \sum_i \lambda_{ij}$$

4) Local productivities

$$A_j = a_j \left[\sum_s \exp\left(-\delta \cdot gt_{sj}\right) N_s^W\, \bar{x}_s \right]^\eta$$

where $gt_{sj} = t_{sj} \cdot \upsilon_{sj} + \tau_{sj}$ is the generalised journey time.

5) Wages

$$w_j = \alpha A_j^{\frac{1}{\alpha}} \left(\frac{1-\alpha}{q_j^W} \right)^{\frac{1-\alpha}{\alpha}}$$

6) Value of time / real wage

$$\upsilon_{ij} = \frac{w_j - \tau_{ij}}{T_j + t_{ij}}$$

7) Residential floorspace demand per OD pair

$$H_{ij}^R = \upsilon_{ij} \frac{\gamma \bar{L}}{\gamma + 1} \frac{1-\beta}{q_i}$$

8) Total residential floorspace demand

$$H_i^R = N_i^R \sum_j \lambda_{ij|i}\, H_{ij}^R = N_i^R \frac{\gamma \bar{L}}{\gamma + 1} \frac{1-\beta}{q_i} \sum_j \lambda_{ij|i}\, \upsilon_{ij}$$

9) Total commercial floorspace demand

$$H_j^W = N_j^W\, \bar{x}_j \left[\frac{(1-\alpha) A_j}{q_j^W} \right]^{1/\alpha}$$

10) Floorspace market clearing

$$H_i = H_i^R + H_i^W$$

11) Equilibrium floorspace price

$$q_i = \frac{1}{1-\psi} \left(\frac{H_i^R}{H_i} + \frac{H_i^W}{H_i} \xi_i \right)^{-1} \left[\frac{H_i}{\left(1 - \frac{H_i}{\overline{\overline{H}}_i}\right) L_i} \right]^{\psi/(1-\psi)}$$

A.2 Data sources for wage and productivity models

Data source	Availability	Owner	Description
Financial Analysis Made Easy (FAME)	Privately owned	Bureau van Dijk	Comprehensive database including financial information of UK companies since 1982, which can be used to derive wage and TFP microdata
Annual Survey of Hours and Earnings (ASHE)	Requires ONS Secure Research Service licence	Office for National Statistics	Survey of organisations representing approximately 1% of UK employees every year since 1997. It can be used to derive wage microdata but the panel dataset is unbalanced.
Annual Business Survey (ABS)	Requires ONS Secure Research Service licence	Office for National Statistics	Survey of organisations representing approximately 2.5% of UK non-financial businesses since 1995. It can be used to obtain GVA, employment microdata, and derive various labour productivity rather than TFP measures. The dataset is unbalanced, although larger organisations are not subject to sampling rotation.
Subregional productivity in the UK	Publicly available	Office for National Statistics	Experimental statistics on local productivity (GVA per hour worked or filled job) available for 179 UK areas (International Territorial Level 3) since 2004, derived from different ONS sources.
Income estimates for small areas	Publicly available	Office for National Statistics	Estimates on annual household income available at MSOA level for England and Wales every second financial year since 2012, which could be used as a proxy of wage data.

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