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The Morphology of a Post-Pandemic City: Applications to London

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Applications to London

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Abstract

Here we extend a hypothetical model used to explore the push and pull forces based on location and interaction in the post-pandemic city to a more realistic context, that of London and its region (Batty, 2021). The abstract model reveals that the mono-centricity and symmetry of the hypothetical city is hard to break until we introduce functions of travel impedance between locations based on a trade-off between the increasing and decreasing attractions of living at a distance from home and/or work. In this way we can reverse the centripetal forces on the centre and in the extreme, wipe these out almost completely with centrifugal forces.

We transfer this analysis to the London metropolitan region, represented by some 1767 small zones where employment is much more concentrated than population. We introduce different levels of lockdown into London by exploring what happens when different proportions of workers work from home and we then slowly relax these restrictions letting the model predict new distributions of employment and population due to a succession of changes in locational attractions due to the relocation of these activities. We do this progressively until everybody is working in their traditional workplace and this indicates that activities are more likely to converge towards the central city than the suburbs. We develop seven different scenarios based on different blends of travel behaviour and these results bear out our experiments with the hypothetical city. We introduce changes in the impact of distance slowly increasing the attraction of places as the lockdown is relaxed and this blows the concentration of activities to the city's edges. We then do the reverse which concentrates the city in its traditional core. There are many issues still to be resolved in using this somewhat more real model of the city than the completely abstract one of the previous paper, but as more data pertaining to the lockdown is gathered and made available, we will continue to improve the model and its analysis.

Note to the Reader: Working Paper 225 'The Socially-Distanced City: Speculation Through Simulation', outlines the hypothetical model applied in this paper to the London metropolitan region and readers who need to note this can find the paper at *https://www.ucl.ac.uk/bartlett/casa/sites/bartlett/files/casa_working_paper_225.pdf*

Introduction

In exploring the form of the future city first as part our control of the COVID-19 pandemic, and then with respect to changes in our locational preferences and travel behaviour, we have developed a model of a hypothetical city form to explore various urban futures in a somewhat speculative but plausible way (Batty, 2021). Despite the various mandates and responses that have changed human behaviour – largely through working from home, the decline in the use of public transport, the deployment of more active travel, and the quest to live in low density urbanised areas, we argue here that there are likely to be longer-lasting changes in travel behaviour in response to the various shocks that have dominated the year 2020. These are will continue through 2021 and perhaps beyond. We do not have good predictive models of the city in any case (Batty, 2018a) so in examining any of a possible array of futures, we must first work with a hypothetical model to which we are able to transfer our findings to a 'semi-real' application based on London and its outer metropolitan area. In fact, there are very few explorations of idealised urban futures using computer models (but see Cecchini and Viola, 1990), largely due to the fact that urban science has not extended much into this realm and because we have not had robust enough technologies so far to explore the future in this way. This is also due to the fact that our intellectual forebears appear to have largely focussed on the visual and literal than the numerical or computational when it comes to cities for very obvious reasons. The time thus seems ripe however to mount such explorations.

In this paper, we will report our experiments with the model on London showing how different scenarios pertaining to travel behaviour can result in dramatic concentration through to massive de-concentration where centripetal and centrifugal forces entangle with one another to produce unusual urban forms. These are not 'ideal' cities *per se* although like such cities, they are hypothetical and provide instruments for exploring a range of possible futures that enable us to think laterally about what the future city might look like. Much of the last century was dominated by urban growth in the form of lower density suburbs although by the 1990s, there were signs of a slow return to the central city, with larger cities beginning to compact a little, and travel being switched to mass transit rather than individualised car use. The pandemic has stopped all this in its tracks with the dominant response being different forms of social distancing at different scales, from people physically keeping at least 2 metres/6 feet apart to increased demands for living at further distances from the city. The dramatic increase in the percentage of the employed population working from home – to a new norm of about 80 percent in the largest cities – has only been made possible by the development of fast and efficient conference systems such as Zoom as well as faster and bigger internet bandwidth. It is most likely that a considerable proportion of his kind of usage will remain after the pandemic comes under routine control, as the disease transforms itself into something more like influenza that can be better managed.

Here we will apply a similar exploratory logic to the future form of London under different scenarios of lockdown release and changing travel behaviour that we used in our hypothetical model (Batty, 2021). Readers do not need to study the previous paper on the design and application of this hypothetical model to understand the current paper for this paper is fairly self-contained. But the wider logic of the exploration is laid out in nine scenarios in the previous paper whereas here there are seven different scenarios all focussing on the release from lockdown and changing travel behaviours. In what follows,

we will first outline the application of the hypothetical model to London, first presenting its calibration to data for the year 2011. We then show the distribution of jobs and residences for different levels of lockdown which in this context imply different proportions of employment working from home. We then define the solution space of possible future urban forms based on three dimensions associated with these parameters: percentage lockdown (λ), the attraction of living at greater distances (α) and the deterrent effects (β) of living further way from any location. We are not able to search the complete space systematically largely because there is no definitive set of comparative measures between different forms that we can optimise as yet but such exploratory analysis does enable us to sharpen our intuitions about what future urban forms might be like.

One major issue with our hypothetical model in the previous paper (Batty, 2021) was our inability to break the symmetry of the system other than by imposing quite radical changes in travel behaviour. The hypothetical model is based on a $n \, x \, n$ square grid whose most accessible point is the centre and whose most inaccessible points are the perimeter cells. The mono-centricity of this system determines its symmetry but on this was layered a hierarchy of employment centres reflecting the typical polycentricity of hubs in most world cities. All this reinforces the symmetry of future forms but to break this, we need to move to real systems that have intrinsic asymmetry. This is the case in London to an extent but as we will see, there is still extremely strong symmetry focussed on the traditional centre which in fact is enormous in size compared to the other employment hubs, much bigger than the hubs used in our hypothetical city. In short what changes we make in travel behaviours are rarely enough to break the overall aggregate symmetry focussed on the central city. In fact, we need better data on spatial variations in the degree of lockdown that we do not yet have to further impress the asymmetry. There is thus a long agenda for further work on the model that we will point to in our conclusions.

Transferring the Hypothetical Simulation to London

In the previous paper, we scaled the hypothetical simulation to a grid of $41 \, x \, 41 = 1681$ zones, and randomised the residential and employment activities in each of these zones in the quest to show that the hypothetical system was somewhat nearer to a real system like London. In fact our London system is composed of some 1767 zones based on small areas called 'wards' which are close to the Census geography of Middle layer Super Output Areas (MSOAs). We prefer to use wards because these are not based on attempting to define areas where the population is of similar size and in this, the wards are more likely to pick up variations in employment; we show these as zone centroids in Figure 1(a). In this system, total population is some 13.428m and employment 6.826m persons with the average population of each zone being 7599 and employment 3863. However these distributions are very highly skewed with the employment distribution having a coefficient of skewness of 12.099, more than 40 times greater than the population which has a value of 0.273. The correlation between these two spatial distributions (employment and population) is also quite low at 0.139. The dimensions of the spatial system defined by its bounding box are 80.228 miles by 72.467 miles where the maximum distance between zone centroids is 82.132 miles.

In terms of the distribution of origins and destinations, the origin distribution which is the residential population is much flatter than the employment distribution with respect to the location of the centre which we can easily glean from the distributions which are shown in Figures 2(a) and 2(b) respectively. In Figure 1(b) we have computed the directional vectors with respect to the dominant trip orientation for each origin zone. These show the predominant orientations in which an average worker at a particular origin zone moves with respect to the journey to work to their destination zones. It is quite clear that the symmetry of the system around the centre is very strong although the polycentric nature of the system is obvious too with respect to towns that have been absorbed into the metropolitan area as it has grown. On the extreme west, we can identify Reading and on the east, Southend on the estuary. Wembley, Heathrow and Docklands – London's second central business district at Canary Wharf – stand out together with Watford, St. Albans and other suburban towns.

a
b
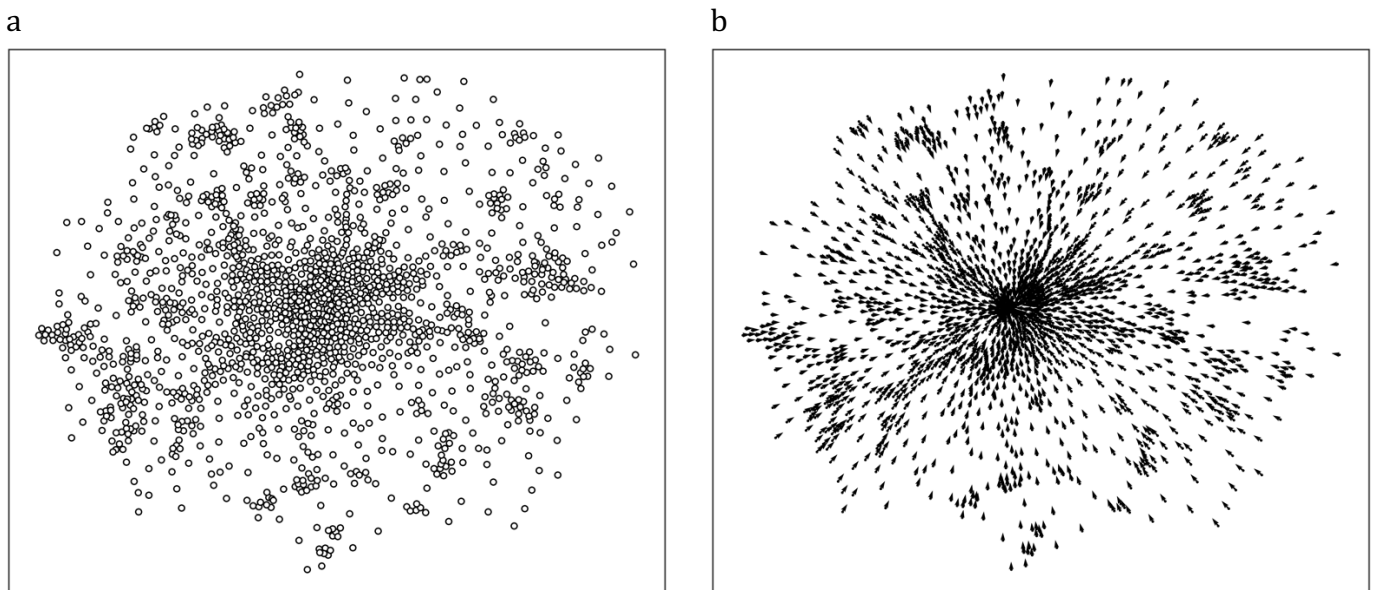
Figure 1: The London Metropolitan Region Data
a) Zone Centroids Based on Wards b) Vector Flow Directions Based on Trips from Residences to Workplaces

a
b
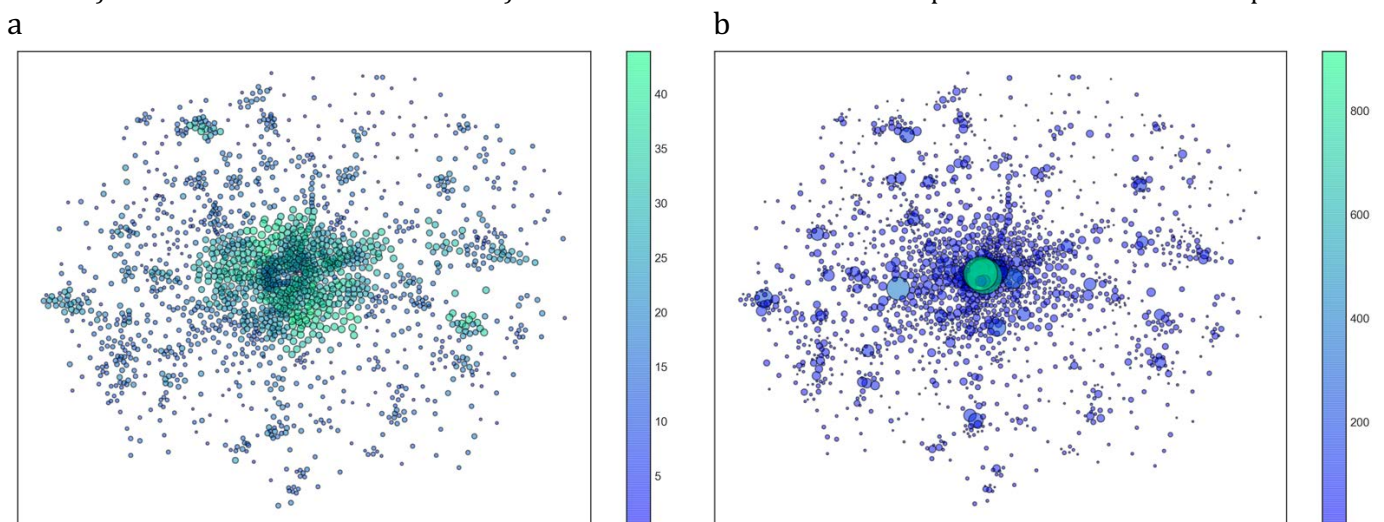
Figure 2: Population and Employment in the London Region
Population at Residences (Origins) of the Journey to Work Trips b) Employment at Workplaces (Destinations) for Journey to Work Trips

From this data which we define as population at zonal origins i, O_i, employment at zonal destinations j, D_j, and trips from origins to destinations T_{ij}, we first calibrate a model of these flows using variants of the classic spatial interaction which we defined in the previous paper. In its simplest form, the model is not constrained to predict known origins and destinations and with this variant, the complete model can be stated as

$$T_{ij} = KO_iD_jd_{ij}^{\alpha-1}\exp\left(-\beta d_{ij}\right) \qquad , \qquad (1)$$

where K is a constant of proportionality. This is defined to ensure that the total number of trips equals that which is observed, which also sums to total employment, that is

$$\sum_i \sum_j T_{ij} = \sum_j D_j = T \qquad , \qquad (2)$$

from which K can be derived as

$$K = T / \sum_i \sum_j O_iD_jd_{ij}^{\alpha-1}\exp\left(-\beta d_{ij}\right) \qquad . \qquad (3)$$

The key function in the model is the attraction-deterrence of distances that is a two parameter gamma-like function where travellers trade-off benefits that emerge as they travel further away from a source – an origin – against the cost that they incur by making such a trip. The component $d_{ij}^{\alpha-1}$ is the attraction where the parameter $\alpha > 0$ while the component $\exp\left(-\beta d_{ij}\right)$ is the deterrent with the parameter $\beta > 0$. This function is essential in that it incorporates an attractor and a deterrent which can be blended in different mixes to replicate different volumes of movement. We currently assume that the model does not have a distance attractor; that is, the default $\alpha = 1$ thus $d_{ij}^{1-1} = 1$ and in this case, distance has a pure deterrent effect.

The model in equations (1) to (3) not only predicts trips but also predicts origin O_i' and destination D_j' activity – locations and well as interactions. Then summing the model over origins and destinations leads to

$$\sum_j T_{ij} = O_i' \quad and \qquad (4)$$

$$\sum_i T_{ij} = D_j' \quad , \qquad (5)$$

We will use this variant of the model to make long term predictions but to calibrate the basic model, we will apply the doubly-constrained variant where equations (4) and (5) predict total origins and destinations which are the same as those used in the model, that is $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$. If the model is formulated in this way, we replace the constant K with two sets of constants, one for origins A_i and one for destinations B_j. Then

$$\left. \begin{aligned} T_{ij} &= A_iO_iB_jD_jd_{ij}^{\alpha-1}\exp\left(-\beta d_{ij}\right) \\[2mm] A_i &= \frac{1}{\sum_j B_jD_jd_{ij}^{\alpha-1}\exp\left(-\beta d_{ij}\right)} \\[2mm] B_j &= \frac{1}{\sum_i A_iO_id_{ij}^{\alpha-1}\exp\left(-\beta d_{ij}\right)} \end{aligned} \right\} \qquad . \qquad (6)$$

We calibrate the model in equations (6) assuming that the gamma parameter $\alpha = 1$, which implies that the attractor effect does not function. We then choose the parameter β so that the predicted mean trip length $\bar{C}$ is equal to the observed mean $\bar{C}^{obs}$

$$\bar{C} = \sum_i \sum_j T_{ij} d_{ij} / \sum_i \sum_j T_{ij} = \bar{C}^{obs} \qquad . \qquad (7)$$

We could have computed the sum of the logs of the mean trip cost and use this to solve for α but in our view, even if this were to give a better calibration, we consider that this effect is largely absent from current pre-pandemic commuting patterns and thus should be excluded from the model at first. In terms of these commuting patterns, the observed mean $\bar{C}^{obs} = 11.514$ miles with the value of $\beta = 0.094$ which we will round up to 0.1 We will keep this value as the baseline for all our experiments.

Apart from incorporating changes in travel behaviour through the gamma function, changes in the numbers and locations of persons working, occasioned by the lockdown ,also provide a means for changing the future form of the metropolis. This is controlled by the percentage of persons still working in their pre-lockdown locations measured by the parameter λ which at the height of the pandemic in London has been (and still is at 22/03/21) around 0.2 whereas in terms of the proportion of persons working from home, $1 - \lambda = 0.8$. To simulate such changes, we essentially keep $(1 - \lambda)$ of the population working from home no longer in their traditional workplaces, and thus the proportion of persons still making trips is λT_{ij}. In terms of the redistribution which occurs when lockdown is initiated, then the number of persons living in the same place is the same while the number of persons working from home consists of those persons who previously travel to work and those who no longer travel but work from home. These changes are defined as follows:

$$O_i = \lambda O_i + (1 - \lambda)O_i \qquad . \qquad (8)$$

There is no difference between these distributions other than the fact that $(1 - \lambda)$ of those who live at a location continue to live there but also work from the same place. This is not the case when we look at the locations of where people work . Only λD_j of the original workplace employment continue to work there while whoever else works at that place also lives there. The total working population at any place j is thus defined as

$$\widehat{D}_j = \lambda D_j + (1 - \lambda)O_j \qquad . \qquad (9)$$

We can easily show what these proportions are in terms of their spatial distribution. The distribution of those at home needs no further comment as this pattern of locations is identical to that we have shown earlier in Figure 2(a). However we can define those essential workers who still work in their usual way and we show this in Figure 3(a). This correlates exactly with the original distribution of employment in Figure 2(b). The distribution of those whose home is now their workplace is shown in Figure 3(b) and this correlates exactly with the original distribution of residential population in Figure 2(a). We construct the new distribution of workplaces by adding the locations in Figure 3(a) to 3(b) to give the distribution $\widehat{D}_j$ which we show in Figure 3(c). The maps in Figures 3(a) to (c) all scale with those in Figures 2(a) and (b) and this opens up the question of whether or not we are able to collect data on variations in the extent to which different

proportions of population and employment are locked down in different locations. Currently we do not have this data but in time, it might be possible to begin to piece this together from diverse sources.

a

c

b
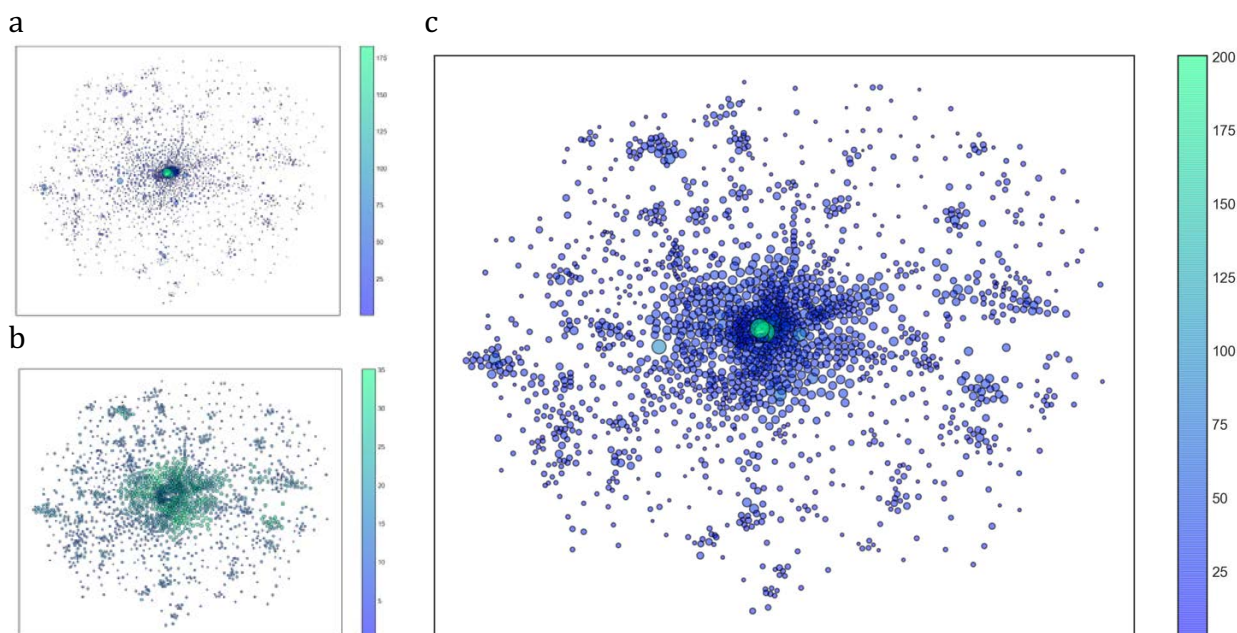
Figure 3: The London Lockdown: 80% Working From Home
a)   Essential Workers at Normal Workplace Destinations b) Nonessential Workers Working from Home c) The New Pattern of Workplace Destinations

Exploring Future Morphologies: Lessening the Lockdown

In our experiments we will start with a simple baseline in which 90 percent of the population are working from home, that is, $1 - \lambda = 0.9$ and we will slowly relax this lockdown until only 10 percent are working from home. The time intervals of the release from lockdown are arbitrary in that they also involve changes in the locational preferences of employment and population which are responses to the changing origins and destinations of workers each time the lockdown level is lowered. In short, for the first 10 time intervals, more and more of the working population and their households become footloose in that they will change their workplace and residential locations as the overall level of lockdown falls. Once $1 - \lambda = 0.1$, we assume that this is the natural level of persons working from home in pre-pandemic times (ONS, 2019). We then continue the simulation for another 20 time periods, letting the employment and population respond to the changing morphology of the city. Once this limit is reached, we consider the model has converged to a new normal and in terms of the processes that the model simulates, this indeed is the case and there is little further change after this time limit has been reached. During the entire period based on $t = 30$ time steps, the travel behaviour is kept at the default level with the gamma collapsed to the standard negative exponential function of deterrence with $\beta = 0.1$ and $\alpha - 1 = 0$.

The assumed equilibrium after 30 iterations is not calibrated to any data pertaining to the speed at which people adjust to the changed distribution of employment and

population and it is thus a long term scenario that represents the notion that the city adjusts immediately to a changed morphology. Our evolution over 30 time steps produces radical change and in some respects is simply an answer to the question: "in a far distant future, how do the forces that move people to different parts of the city play out?". In fact we can write the model formally as follows where we index the variables with respect to the time steps as

$$
\left.\begin{array}{c}
\hat{T}_{ij}(\lambda_{t+1}) = \lambda_{t+1} K(\lambda_{t+1}) \hat{O}_i(\lambda_t) \hat{D}_j(\lambda_t) d_{ij}^{\alpha(\lambda_t)-1} \exp\big(-\beta(\lambda_t) d_{ij}\big) \\[2mm]
\hat{O}_i(\lambda_{t+1}) = \sum_j \hat{T}_{ij}(\lambda_{t+1}) + (1 - \lambda_{t+1}) O_i \\[2mm]
\hat{D}_j(\lambda_{t+1}) = \sum_i \hat{T}_{ij}(\lambda_{t+1}) + (1 - \lambda_{t+1}) O_j
\end{array}\right\} \quad . \quad (10)
$$

In terms of the model in equations (10), it is clear that this is unconstrained and at each time step, new origin and destinations activities are predicted as $\hat{O}_i(\lambda_{t+1})$ and $\hat{D}_j(\lambda_{t+1})$. The lockdown parameter λ_{t+1} varies from $\lambda_1 = 0.1$ to $\lambda_9 = 0.9$ and from λ_{10} to λ_{30}, this value is fixed at the maximum numbers working from home as $\lambda = 0.9$. The parameters that govern behaviour with respect to travel are $\alpha(\lambda_t) - 1 = 0, \forall t$ and $\beta(\lambda_t) = 0.1, \forall t$.

There are a number of statistics that we will compute for each of our scenarios and these relate to the morphology of the predicted city at each stage of its evolution. We will start with the mean trip length defined in equation (7) as $\bar{C}$ which is an average of the amount of travel a typical trip-maker makes in the system, measured in miles. We also have four measures of how employment and population are related spatially. At any time t, we measure the coincidence between the origin activity and destination activity from

$$
\Psi(\lambda_t) = \sum_i \left| \hat{O}_i(\lambda_t) - \hat{D}_i(\lambda_t) \right| \quad . \quad (11)
$$

This measure is zero if the two distributions are the same. We can also speculate that if all the employment is in one place and all the population in another, then this measure would be at a maximum. What we will find is that in some scenarios, these two distributions do converge towards the zero value. Another very simple measure is the correlation between the initial pandemic origin and destination activities with respect to their distributions at any time period. Therefore we can compute the correlations between O_i and $\hat{O}_i(\lambda_t)$ and D_j and $\hat{D}_j(\lambda_t)$ and these give measures of how close the equilibrium outcomes are to the initial distributions at each stage of the simulation. Lastly we measure the relative spread of the origin activity from the centre of the city where a large proportion of the activity is initially located. This is a measure of weighted distance

$$
\Phi^D = \sum_i \hat{O}_i(\lambda_t) d_{i,122} / N \quad , \quad (12)
$$

where $d_{i,122}$ is the distance from any origin zone i to a central zone (in the case of London, the Holborn-Covent Garden ward, zone [122]). If everybody lived there this measure would be a minimum while if everybody lived at a maximum distance in the spatial system from this zone, the measure would be at a maximum. As such, this is a crude measure of suburbanisation.

We will first present the baseline Scenario 1 as we have defined it here. We show the distributions of origins and destinations once the lockdown is completely released (at $\lambda_9 = 0.9$) in Figures 4 (a) and (b) and we continue with the evolution to equilibrium in Figures 4(c) and (d).

a

b

c

d
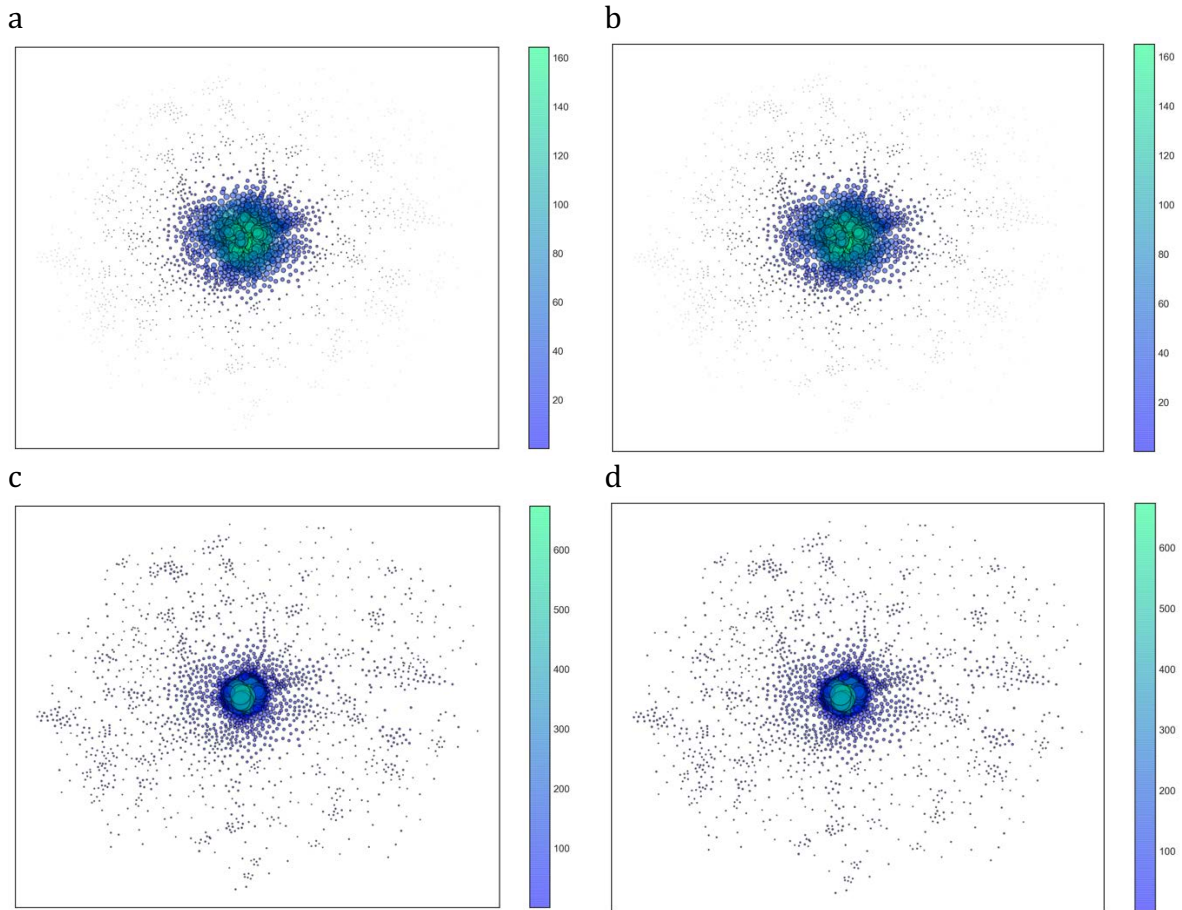
Figure 4: Scenario 1: Transforming the Old Normal Through Returning to Work and Restoring Relocation
a) Origins, then b) Destinations after 10 Iterations; c) Origins, then b) Destinations after 30 Iterations

Comparing Figure 4 with the earlier data in Figures 2 and 3, it is clear that starting with $\lambda_1 = 0.1$ where the mean trip length is about 11 miles, then as the lockdown comes off, the trip length falls systematically to around 4 miles. The morphology tends to concentrate, almost implode in on itself and you can see the individual centroids become denuded of activity as this all flows to the traditional and geometric centre of the city. We show all these statistics for all our scenarios in Figure 5. In fact the difference measure $\Psi(\lambda_t)$ first converges but then begins to diverge although the differences are relatively small. When we look at the correlations $r\{O_i, \hat{O}_i(\lambda_t)\}$ and $r\{D_j, \hat{D}_j(\lambda_t)\}$, for the origins these get progressively more smaller with respect to the original distribution but they do stabilise at around 0.25. The destination correlations decrease slightly at first and then increase as the new normal destination activity is restored to its more traditional pattern (see Figure 3) with the employment distribution becoming closer to the initial distribution. The last measure of suburbanisation Φ^D systematically gets smaller and this indicates that the city is becoming ever more concentrated in terms of employment. To

9

an extent this is quite counter to the notion of working from home but to an extent it implies that residents and workers continually adjust their locations to gain the benefits of locational attraction in terms of size, with population living closer and closer to its place of work, whether that be working from home or at traditional places of work. We might use Φ^D as an index of suburbanisation and in the default case this varies from the baseline of about 59409 to the compact city form where it reduces to 19480.
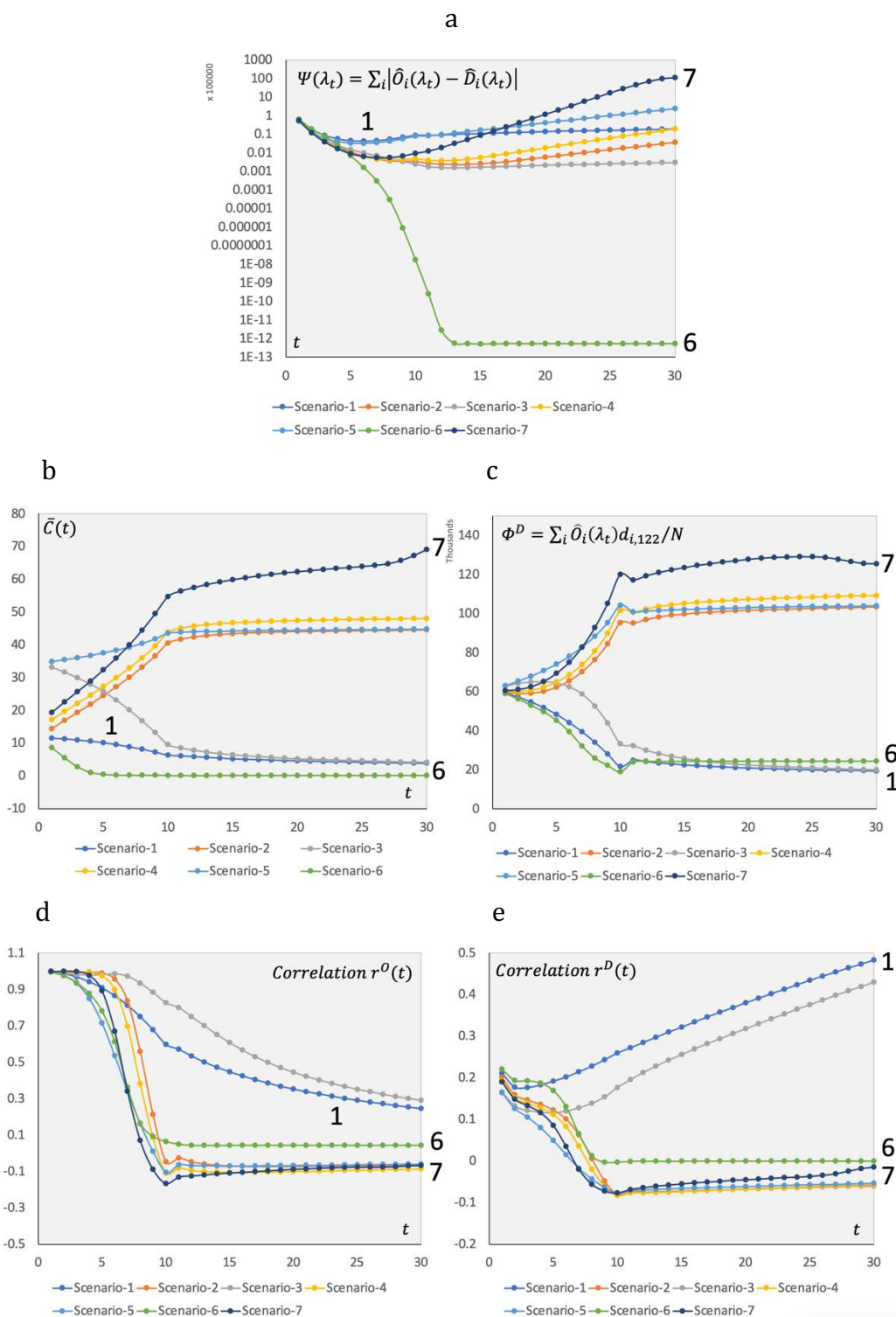

Figure 5: Statistics of the Transition Back to Working in Traditional Workplaces and Continued Responses to the Redistribution of Residential Locations and Workplaces

Changes in Travel Behaviour Generating New Morphologies

Our first experiment and all subsequent applications involve changing the parameters defining the attractor-deterrence function, where here in the second scenario, we focus on increasing the value of $\alpha - 1$ from 1 to 6 and keeping β at 0.1. This systematically pushes people away from their workplaces and we might expect a strong degree of suburbanisation to take place with both origin and destination activities moving from centre to periphery. The mean trip length increases quite rapidly as both more people come out of lockdown and revert to traditional work patterns and as the attraction of living further distance from work continues to increase, converging at around a mean distance of more than 40 miles. This as one might expect pushes both employment and population to the periphery of the system. When the old normal with respect to work has been restored after some ten time periods, although activity continues to decentralise, the patterns does not change much more as the new equilibrium emerges. We show the distributions at $t = 10$ and $t = 30$ in Figure 6. The suburban pattern becomes established quite early in the process with the Φ^D measure doubling from some 59830 to 103373. The correlations between origins and between destinations completely disappear – they move towards zero correlation – by the time the final pattern emerges while the coincidence of locations between employment and population also increases substantially, even though the movement is into the periphery with the central city dramatically decanting its employment and population to the edges of the system.
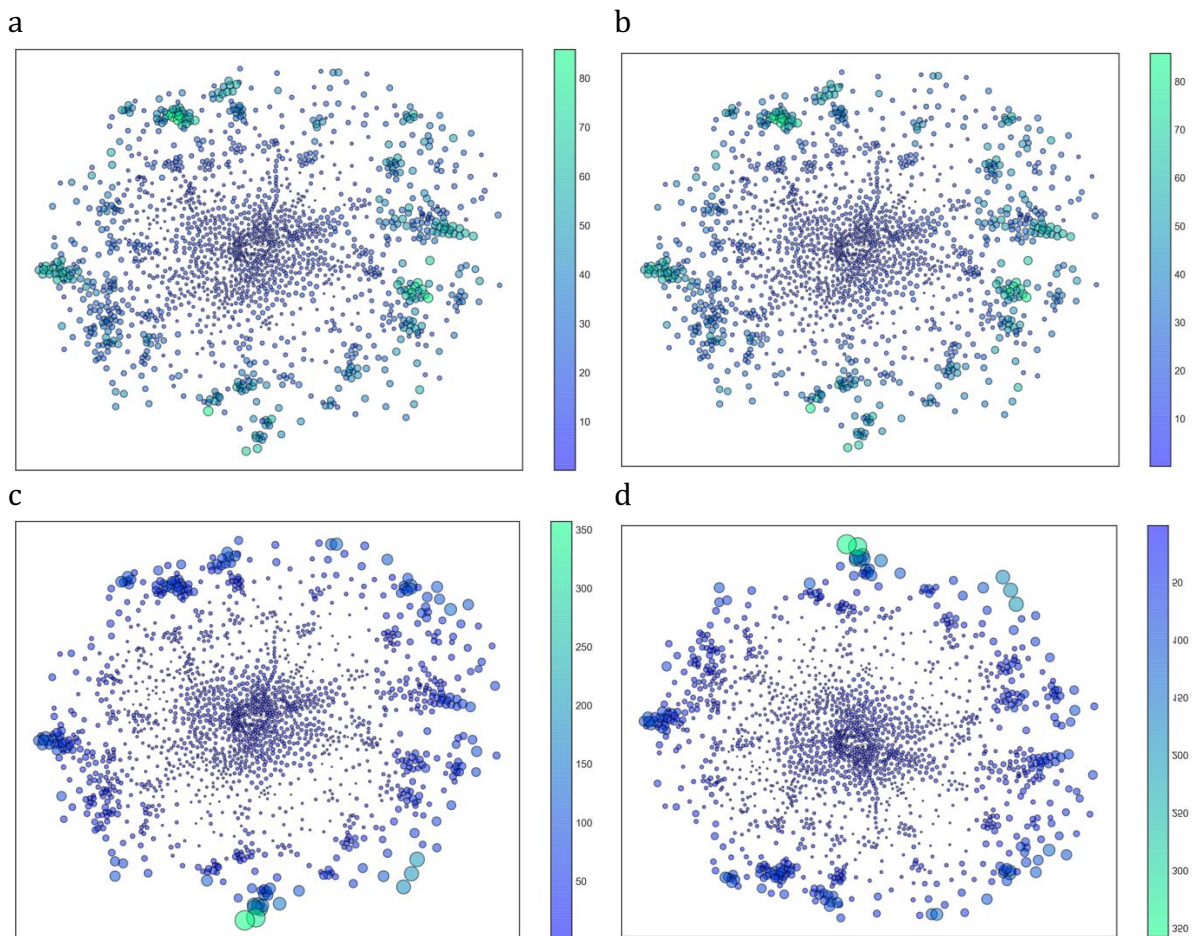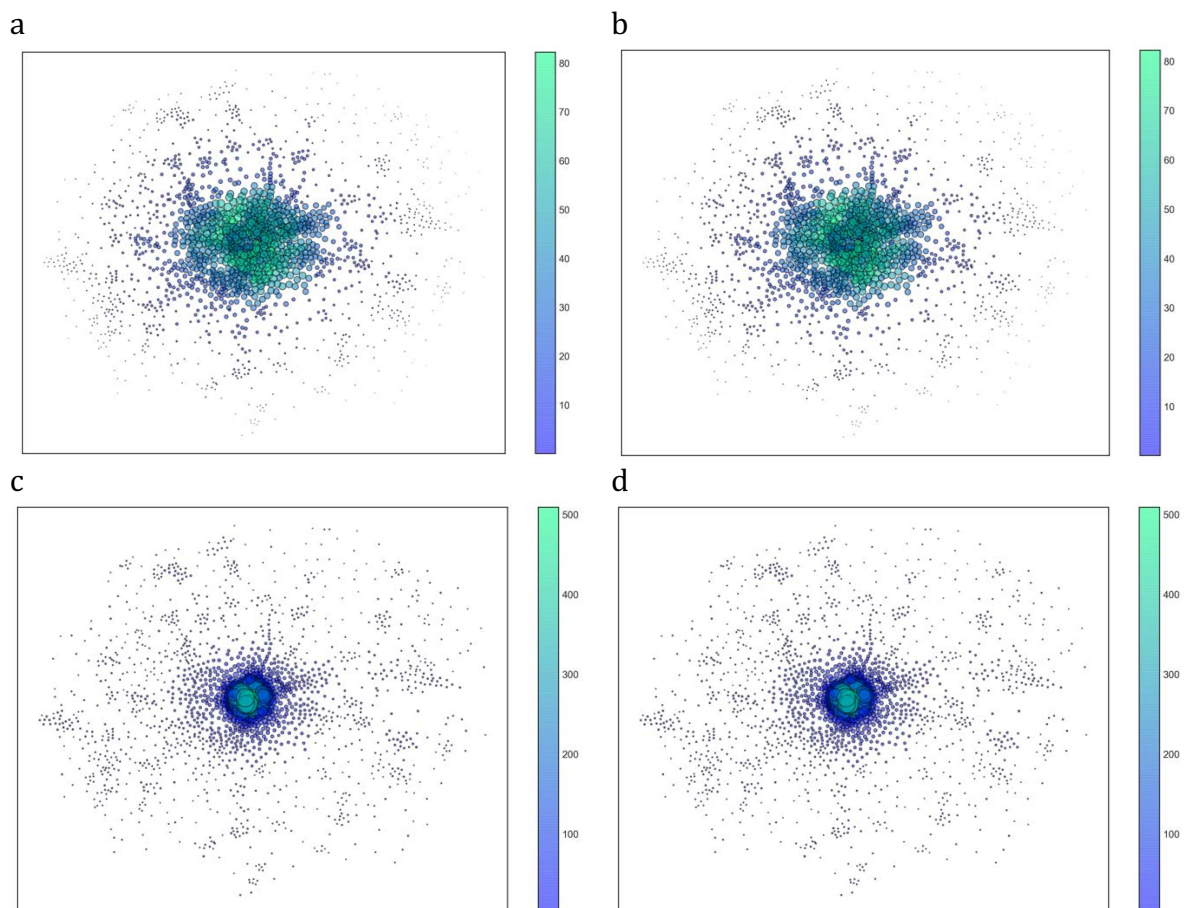

Figure 6: Scenario 2: Reducing the Deterrent Effect of Distance Using the Gamma Function
a) Origins, then b) Destinations after 10 Iterations; c) Origins, then b) Destinations after 30 Iterations

Although we cannot comment on this in detail, as activity is attracted from the core to the periphery, it tends to cluster in the bigger locations such as Reading, Southend, the Heathrow sprawl, Watford and similar edge-city like locations. The next Scenario 3 also changes travel behaviour but in the opposite direction to that introduced in the previous scenario. What we do with this example is to assume that populations change their behaviour during lockdown to the point where they first wish to live far from their traditional workplaces. We start the sequence at $t = 1$ with a strong attraction to living further away and as the lockdown comes off, this effect through the gamma function reduces to the point where this function has no effect; that is, $\alpha - 1$ goes from 6 to 1 keeping β at 0.1 as before. The pattern that we show in Figure 7 does not differ markedly from the baseline in Figure 4. The average trip length is now 33 miles at the start and this reduces to 4 miles when $t = 30$. The correlations have the same pattern as in the baseline while $\Psi(\lambda_t)$ falls dramatically as the employment and population patterns cluster very tightly. The index of suburbanisation also falls from 62919 to 20068 with the implication that in the steady state there is likely to be complete convergence on the centre for both population and employment.
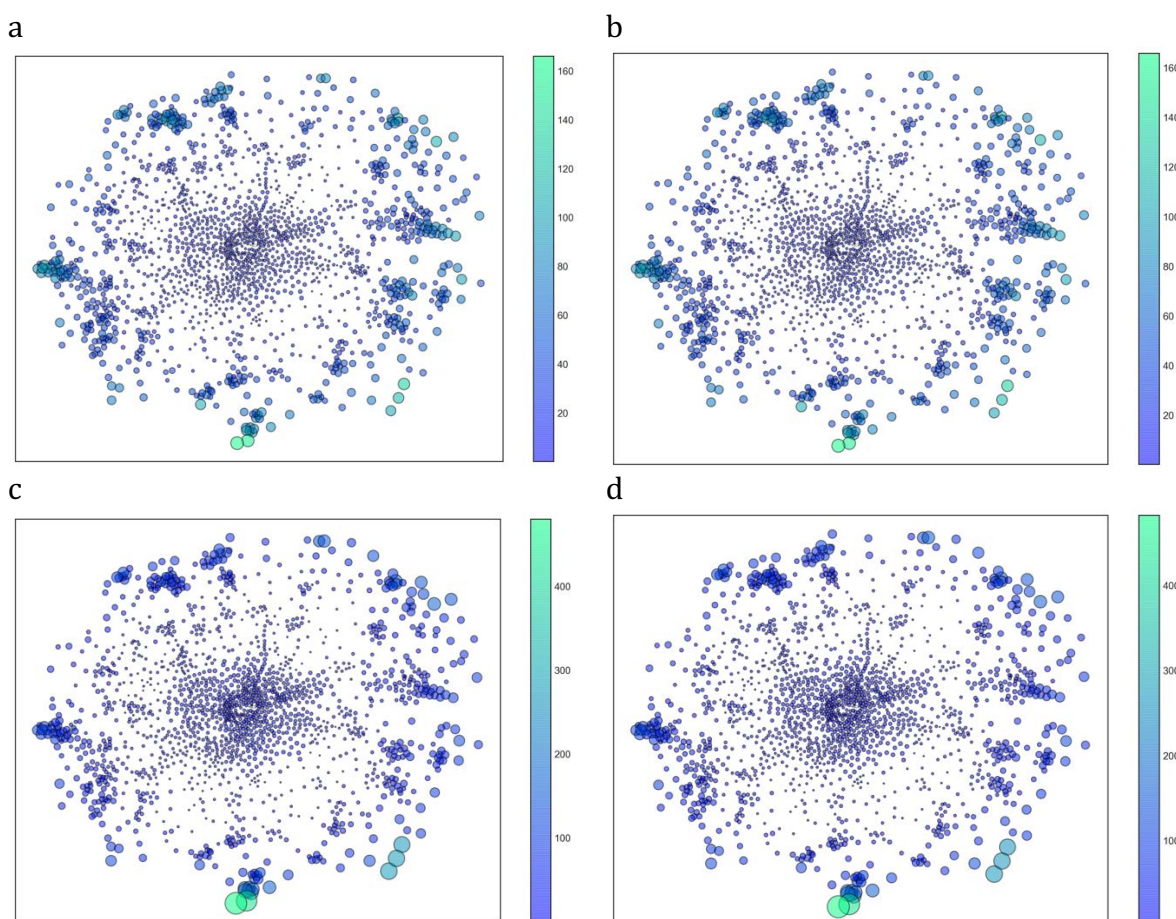
a

b

c

d

Figure 7: Scenario 3: Returning to Work With Decreasing Preference for Living at a Distance

a) Origins, then b) Destinations after 10 Iterations; c) Origins, then b) Destinations after 30 Iterations

We have also strengthened the attractor effect of the gamma function by increasing the parameter $\alpha - 1$ to 6 for the duration of the simulation and the statistics are shown in the graphs in Figure 5 as Scenario 4. We will not show this example visually for the next one which keeps the gamma parameter constant, reflects a one-off transition from the pre-

pandemic travel pattern to the regulated pandemic. This leads immediately to a distinct aversion to living near one another as reflected in the attractor-deterrent function. We assume that the gamma parameter is set unerringly at a value of $\alpha(\lambda_t) - 1 = 6, \forall t$ keeping $\beta(\lambda_t) = 0.1, \forall t$. This is reflected in what we know about the scenario reflected in Figure 6 and the results are similar as an examination of the statistics in Figure 5 reveals. We show these outputs for $t = 10$ and t=30 in Figure 8 and the statistics in Figure 5 show that the mean trip length adjusts almost immediately to 30 miles and eventually converges to a very stable value of 44 miles. In fact, the correlations of origins with destinations gets smaller throughout the simulation while the correlations both sink to zero. The suburban index Φ^D also increases from 63115 to 103927 which is extremely stable as the relevant trajectories in Figure 5 indicate. Last but not least, there is clear indication from Figure 8 that it is the south of the system on its periphery that looks very attractive for development and in our last scenario below we will return to this feature of the simulation

Figure 8: Scenario 5: Returning to Work With Significant Preference for Living at Distance
a) Origins, then b) Destinations after 10 Iterations; c) Origins, then b) Destinations after 30 Iterations

The best way to explore these different scenarios is interactively and this is of course possible with this model that can be ported to a variety of interfaces that allow continued experimentation such as in a Jupyter notebook. However we cannot demonstrate this here but we will conclude by showing two more extreme scenarios. What we have done is reverse the effect of the gamma attractor by specifying a negative parameter value $\alpha(\lambda_t) - 1 < 1$ which we set at –6 . Almost immediately even before the population

returns to its traditional workplaces, the mean trip length collapses as people essentially abandon any long distance travel. By the end of the lockdown, people have adjusted their work journey patterns to reflect a very close home-work balance. The system compacts itself dramatically and there is zero correlation with the pattern of London's population as presented in Figures 2 and 3. Essentially people live and work in the same place as we show in Figure 9. By the time everyone has returned to their traditional work, this has all concentrated in the centre of the system. These patterns look very strange in that the symmetry of the system has more or less disappeared to be replaced by an intense monocentric focus.
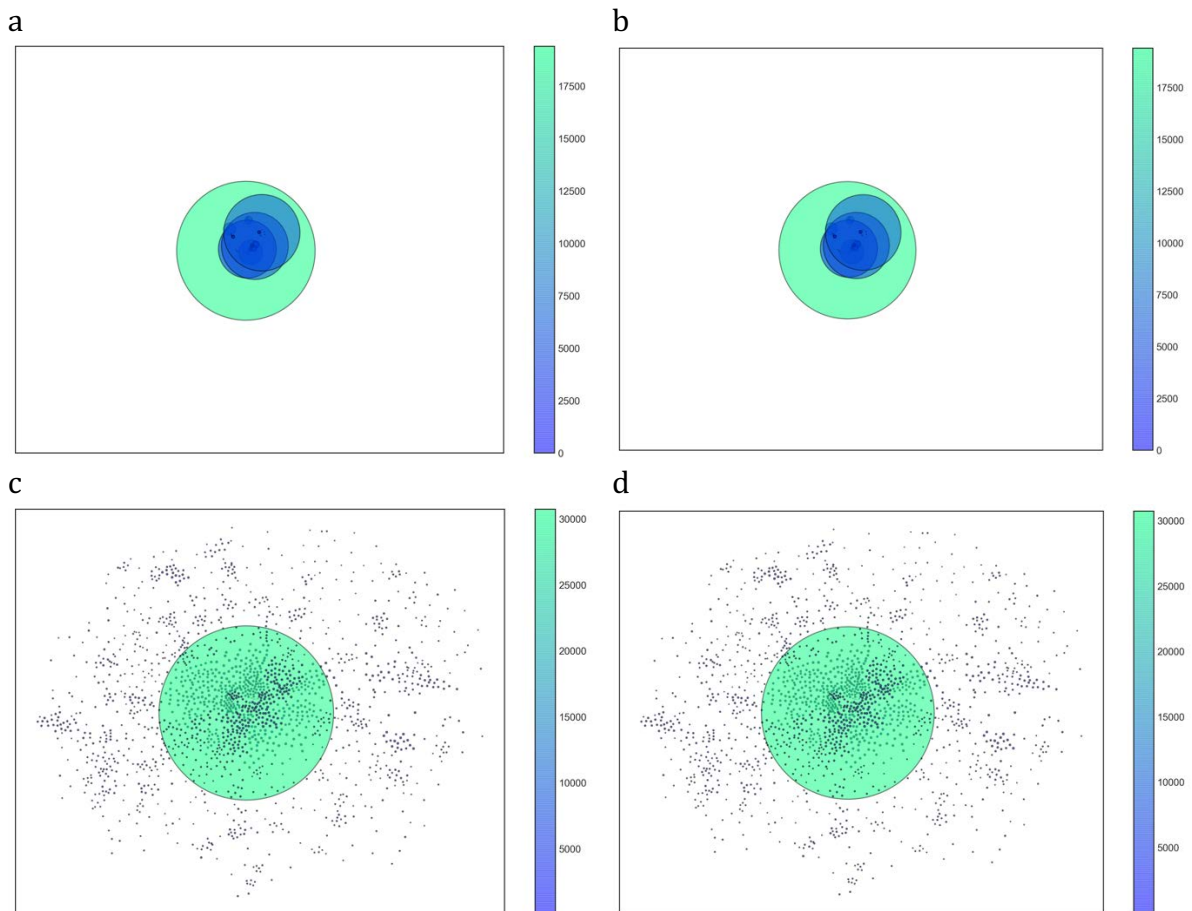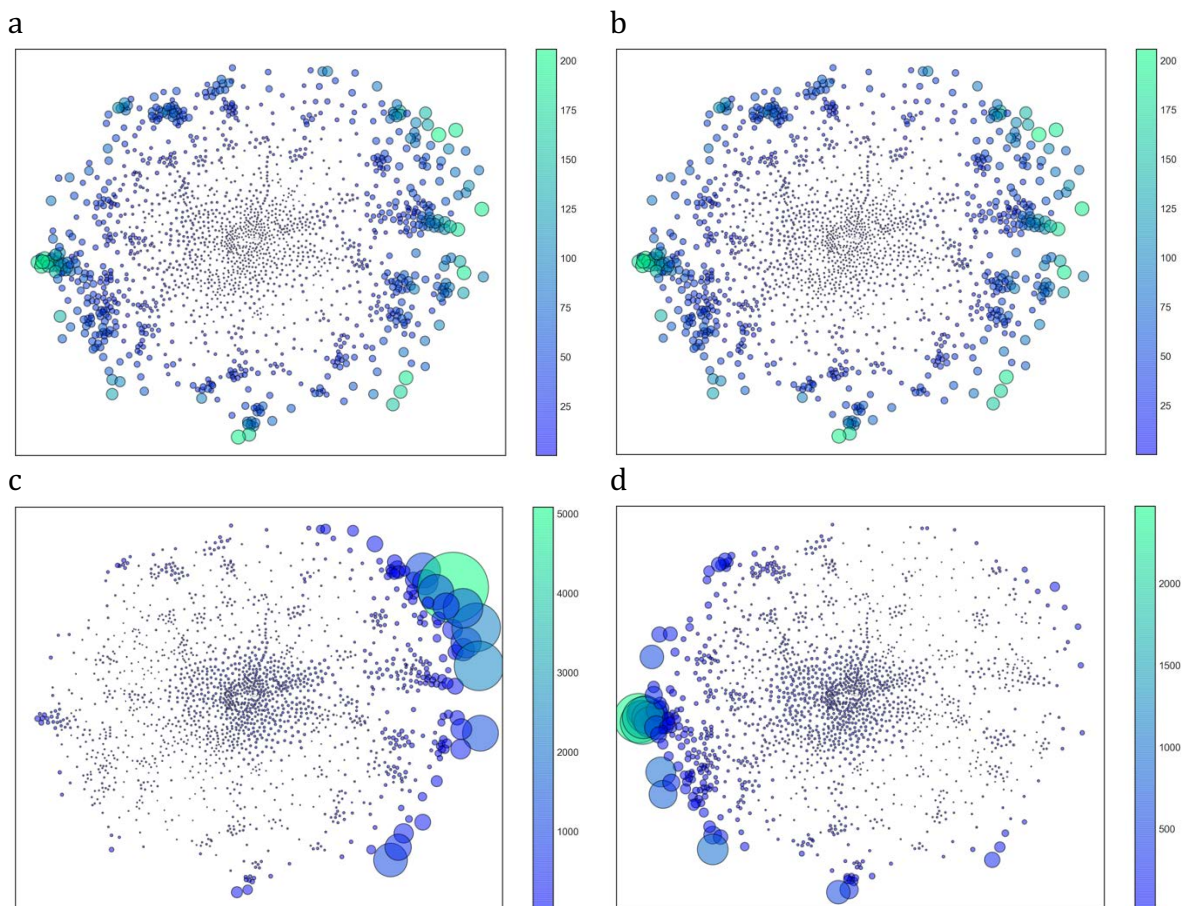

Figure 9: Scenario 6: Increasing Resistance to Locating at a Distance Between Home and Work
a) Origins, then b) Destinations after 10 Iterations; c) Origins, then b) Destinations after 30 Iterations

Our last example takes the model where we specify an increasing preference for living at a distance which we simulated in Scenario 2 and we then halve the value of the β parameter. This reflects the increasing attractor on distance and it also lowers the impact of the deterrence effects, thus embodying a double impact on pushing population and employment at increasing distance from one another other. The mean trip length varies from 19.350 to 69.150 miles and this produces an extreme pattern where the majority of the population at origins live on the east and north east of the metropolis while employment is strongly clustered in the Reading-Heathrow area in the west of the system. The distances that connect these locations are amongst the maximum that exist in the system and we have explored what happens when the simulation continues indefinitely;

the model pushes all the population to one location on the east and all the employment to a single location on the west. Moreover this is one of the most extreme kinds of suburbanisation that is possible, notwithstanding that it is highly unrealistic in its form, if not its function.

a

b

c

d

Figure 10: Scenario 7: Reducing the Deterrent Effect of Distance Using the Gamma Function Starting with Double the Observed Mean Trip Length in Scenario 2
a) Origins, then b) Destinations after 10 Iterations; c) Origins, then b) Destinations after 30 Iterations

Further Experimentation: Next Steps

Before we reflect on how we might take this analysis forward, it is worth looking at the various trip patterns associated with these morphologies. This could be pursued at a level of an analysis where we map the distribution of trips T_{ij} into their origin and destination summations $\sum_j T_{ij} = O_i$ and $\sum_i T_{ij} = D_j$. In fact, despite voluminous work on spatial interaction, there has been very little analysis of the patterns that make up such structures and trip distributions are very difficult to visualise (Batty, 2018b). In the previous paper (Batty, 2021), we introduced the notion of summaries of trip distributions using vector fields and we illustrated the field for London at the beginning of this paper in Figure 1(b). In fact the directional structure of trips in the London region in this figure is remarkably stable, just as it was in the hypothetical model we explored under similar conditions. In our previous paper, we found it extremely difficult to effect any symmetry

breaking for the hypothetical model. The same is true here and all of our scenarios with the exception of the last two, 6 and 7, the most extreme, generate a pattern of symmetry almost identical to that in Figure 1(b). Scenario 6 which generates complete concentration at the centre of the city completely destroys the symmetry of all the zones outside the centre and we show this in Figure 11(a) which is not unlike a field of iron filings when the magnetic force is removed. The directions appear to be fairly random and what symmetry still exists is largely due to the fact that the system is broadly elliptical with a well-defined focal point.
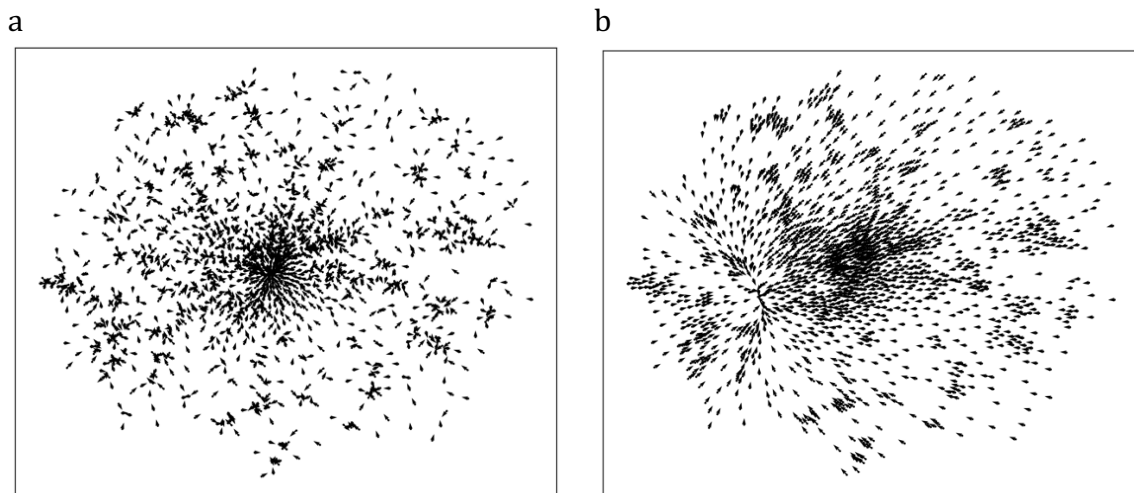
a   b

Figure 11: Directional Trip Vectors for Scenarios 6 and 7, after 30 Temporal Iterations
a)   Scenario 6 where there is no longer any distinct focus b) Scenario 7 best explained as a field with major attractions south west and east north east.

The last scenario is formed by halving the value of the negative exponential parameter β and this increase the mean trip length massively. If we let that simulation continue for 100 iterations, then the collapse is complete and centre of the system shifts even further to the south west. It is difficult without good analytical tools to disentangle trip distributions which make sense of the vectors in Figure 11(b) and this is certainly a major analytical issue that needs resolving in further spatial interaction research.

In the previous paper (Batty, 2021), we implied that a systematic search of the solution space defined by the two parameters of the gamma function $\alpha - 1$ and β was unlikely to yield any surprising results largely because of the strongly symmetric structure we had designed artificially. We concluded that we needed to break symmetry and one obvious way to do this was to move to a real system. As seen in Figures 1 and 2, this is certainly the case when we move to the London application but so far in this paper, we have not augmented our solution space with features and variables that are useful in defining some form of optimum morphology. This in fact is our longer term quest but to do so, we will need to enrich the analysis with some definite and agreed features that all urban morphologies should meet. For example, limits on trip lengths, densities, and accessibilities all imply different costs and benefits and to embrace this we will need to extend the model. However we still need to keep the model relatively parsimonious, judiciously extending our solution space in a way in which we would hope to find optimum solutions.

One clear way is to search for better data on the relationships between urban location and the percentage of persons locked down at work and home and this will undoubtedly provide further symmetry-breaking as well as attributes that change travel patterns on a more local basis than the analysis in this paper reveals. We also need to explore the whole question of the long term behaviour of the model proposed here – the implied equilibrium which Lowry (1964) many years ago referred to as an 'instant metropolis'. As the pandemic comes under control, the situation concerning travel patterns and preferred locations will continue to change and as yet, all we have from this paper and other speculative commentary, is some sense that the city is unlikely to explode to its edges and that there will be some return to the central city.

What this and our previous paper have illustrated is that the effect of symmetry in cities with any longevity whatsoever, is so strong that widespread suburbanisation after the pandemic ends is unlikely. Layers and layers of history have reasserted this symmetry and it is unlikely all this will be done way with almost overnight. In fact the notion of treating the city in layers like this is quite consistent with the notion of populations being locked down and in our future work, we will begin to think of our model of the city as consisting of layers which have different behaviours. This is perhaps not so different from disaggregating the population but treating these as behavioural layers may provide a fruitful model for thinking about how cities might evolve and how we might begin to regulate and manage them. This then is our prospect. Many readers may be uncomfortable with this mixture of the hypothetical and the real but this is no more nor less than thinking out-of-the-box with respect to what future cities might be like. We now have the technologies to pursue this and to complement our thought experiments with computer simulations.

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