**Introduction**

A city’s vibrancy, productivity, efficiency and innovation depend in large part on how effectively it can connect job opportunities and workers to each other through economic, social, intellectual and physical networks (Bettencourt & West, 2010). An approach to urban planning that integrates land use distribution and transportation strategies can facilitate this by maximising job accessibility (that is, matching the distributions of workers’ home locations and job opportunities to overcome spatial and temporal distance), so that the available transportation capacity can be used most efficiently to maximise the range of job opportunities that workers can access within reasonable travel times (Hansen, 1959).

An understanding of the macro-scale spatial patterns in workers’ accessibility to jobs is an important first step for identifying and prioritising problem areas, and optimising and coordinating intervention strategies (Geurs & Wee, 2004). However, it is also important to keep in mind that job accessibility varies across many dimensions besides space (Lucas, 2012). In particular, accessibility levels are affected by the characteristics of workers and jobs (for example, depending on their skills, salary and industrial sector, not every job is equally attractive or suitable for every worker) and by day to day fluctuations in transport network performance (travellers need to account for a margin of uncertainty around potential arrival times when deciding how and when to travel).

This study aims to carry out an analysis of job accessibility by public transport in London that better accounts for this multidimensional nature. I develop a typology of neighbourhoods that categorises them by overall job accessibility, the sectoral mix of their available jobs, the relative social deprivation of their working-age population and travel time reliability. In addition to providing insights into how land use and transport interventions can adjust the large-scale spatial structure of London to improve job-worker spatio-temporal matching, the results can also provide guidance for where to focus measures that improve workers’ skillsets, encourage job growth in certain sectors and improve public transport reliability, thus allowing for closer coordination of strategies across a wider range of domains.

**Literature Review**

Hansen (1959) defines accessibility as a measure of the potential for interaction between people and the opportunities that they seek. This is a function of how people and the relevant opportunities are distributed across space and the cost of travel (or connectivity) between different locations. In his original conceptualisation, accessibility increases as the number of opportunities near a person increases and as the cost of travelling to the opportunities decreases.

Based on this definition, researchers have developed a wide range of indicators to analyse accessibility (Geurs & Wee, 2004). Of these, “location-based” measures are most frequently used for city-level analyses, because they treat accessibility as a property of different areas (as opposed to a property of travellers or of components in the transport network) and thus can be used to spatially aggregate and visualise the distribution of accessibility. In general, analyses of job accessibility using these measures have found wide within-city variations (Shen, 1998; Sanchez, 1999; Kotavaara, et al., 2012; El-Geneidy, et al., 2016; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Deboosere & El-Geneidy, 2018). This is largely because job distributions tend to be highly clustered and connectivity is unevenly provided, as areas with higher density tend to generate more trips and thus tend to be better connected with faster, higher-frequency transport links.

One drawback of location-based accessibility indicators is that they match workers to jobs as if every worker and every job were interchangeable. To capture how accessibility levels vary across different types of workers and jobs, some studies separately measure accessibility for subsets of workers (such as low-income workers) matched to the jobs that are suitable for them (like jobs in sectors that tend to pay lower wages) (Shen, 1998; Deboosere & El-Geneidy, 2018), while others examine how accessibility levels to all jobs vary by area-level indicators of social disadvantage (such as neighbourhood average income or an index that summarises multiple dimensions of social deprivation) (Sanchez, 1999; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018). These analyses have found that most cities have areas where more disadvantaged residents are burdened with poorer accessibility to jobs, though this seems to be a more systematic problem in poorer cities with less extensive public transport systems.

In the context of London, Ford et al (2015) showed that job accessibility varies significantly across space, but as far as I am aware there has not been a published analysis of how job accessibility varies across different types of workers and jobs. Nonetheless, both the UK government (Social Exclusion Unit, 2003) and the Greater London Authority (GLA) (2018) recognise that low accessibility may significantly hinder disadvantaged residents’ access to jobs as well as other services like healthcare, education and leisure, thereby constraining their options, increasing travel burdens, lowering quality of life and entrenching social deprivation. To make the situation fairer, authorities recommend targeting accessibility improvements to better connect areas with more disadvantaged residents to the opportunities they need.

Researchers have also increasingly recognised that the spatial distributions of workers, jobs and connectivity can all vary significantly over time (Tenkanen, et al., 2016; Järv, et al., 2018; Hu & Downs, 2019). Using geolocated social media or mobile phone data, workplace opening times and public transport schedules, researchers have built time series of these three distributions over a typical day and calculated accessibility measurements for each area at each time point. However, these studies calculate accessibility based on “typical” (mean or ideal) values of these variables at each time point, without accounting for the stochastic distribution of possible values around the typical values. In particular, these studies use a single value to represent the travel time between any two locations, and thus do not capture the margin of uncertainty around travel times that travellers actually need to account for deciding when and how to travel.

Efforts to analyse travel time reliability have been hindered by a scarcity of data on the stochastic distributions of travel times at the level of each trip, due to the labour intensiveness and expense of traditional methods to collect such data (such as floating traveller surveys, in which a person repeatedly conducts a trip at the same time over different days and records the time needed to complete it). However, recent advances in large-scale data collection and dissemination in public transport systems, such as through systems for automatic fare collection, automatic vehicle location and real-time trip planning, have overcome this scarcity and allowed for travel time distributions to be measured at very fine levels of spatial and temporal resolution (+ citation). On the basis of these new capabilities, Uniman et al (+ citation) defined the concept of the Reliability Buffer Time (RBT), which is the difference between the 95th percentile of travel times (representing an unusually slow trip) and the median travel time (representing a typical trip) between each origin-destination pair, and reflects the extra time that a traveller needs to budget into her trip in order to be 95% certain that she will not arrive late on any given day.

In light of the existing literature, this study is positioned to make several contributions to the analysis of job accessibility. Firstly, it will conduct a multidimensional job accessibility analysis of London that better captures how accessibility levels vary among working-age residents and jobs with different characteristics. Secondly, it will also consider how travel time reliability affects different areas in London, adding a novel dimension to accessibility analyses. In the next section, I present the methodology of this study and the data sources I will use.

**Study Design and Data Sources**

This analysis will focus on accessibility to jobs from working-age residents’ home locations. Even though not all trips (even during peak hours) are commutes from homes to work, home-based work commutes are a primary driver of travel demand during peak periods, and thus significantly shape the layouts and operations of public transport networks. In addition, most of the opportunities that people seek (such as education, healthcare or shopping) also provide jobs, so accessibility to jobs will at least somewhat capture accessibility to opportunities in general (Deboosere & El-Geneidy, 2018, p. 56).

*Data on the Spatial Distributions of Jobs, Workers and Social Deprivation*

MSOA-level counts of working-age residents (those aged 16 to 64) and jobs for 2017 were obtained from the Office of National Statistics (+ citation). Job counts are disaggregated by Standardised Industrial Classification Code (SICC), allowing for sector-specific analyses of the job distribution. Unfortunately, counts of residents that are disaggregated by sociodemographic characteristics (like educational qualifications, income or disability status) are only available from Census data, which are 8 years out of date at the time of this study.

In the absence of such disaggregated population count data, many researchers use location-based aggregate measures to reflect spatial disparities in sociodemographic characteristics, such as neighbourhood average income (Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018) or an index combining multiple dimensions of social disadvantage at the local scale (El-Geneidy, et al., 2016; Deboosere & El-Geneidy, 2018). In the UK, the Department for Housing, Communities and Local Government (DHCLG) has developed the Indices of Multiple Deprivation (IMD) (2015) to reflect the relative degree of social deprivation experienced by residents in small areas across a wide range of domains, including income, employment, health, education, crime, housing and the living environment. In this study, I use the IMD data to capture the spatial variations in social deprivation among the working-age population, and I follow the DHCLG guidance to focus on the relative ranking of the areas by IMD index scores, rather than on the raw scores themselves.

*Measuring Job Accessibility with Job Provision Ratios*

Location-based accessibility measures are attractive as they can be easily used to spatially aggregate and visualise accessibility levels. The simplest location-based measure reports accessibility in terms of “cumulative potential” (Geurs & Wee, 2004, p. 133), summing up the total number of jobs that can be physically reached from each area within a certain travel time (the area within a certain travel time of a location is known as its “catchment”). Essentially, this is the dot product of 2 components, , where:

1. O is a column vector of length n:

where oi is the number of jobs in one of the n areas i, and;

1. C is a n by n matrix of weights:

where ci,j is the cost (in this study, time) of travelling from area i to area j, and f(ci,j) is a function that decreases as ci,j increases. Thus, f(ci,j) indicates the ease of travel from i to j.

However, such a measure treats accessibility to jobs as non-excludable; that is, the fact that a particular worker can access a job does not deprive any other workers of the ability to access the same job. This does not reflect the reality that each job typically can only be occupied by one person. To address this theoretical drawback, adjustments were proposed by Shen (1998) and elaborated in the public health literature as the “two-stage floating catchment area” method (Luo & Wang, 2003; Luo & Qi, 2009; Wang, 2012) to account for:

1. The spatial distribution of working-age residents, stored in a column vector P of length n

where pi is the number of working-age residents in one of the n areas i.

Then, the accessibility values, stored in a column vector R of length n, are obtained by:

where gives the weighted sum of the number of working-age residents within each area’s catchment, divides element-wise the number of jobs in each area among the weighted sum of working-age residents within its catchment, and is a weighted sum of the number of jobs provided by each area to each working-age resident within its catchment. The resulting quantities in the matrix R can be directly interpreted as ratios allocating jobs within each area’s catchment to working-age residents, and express accessibility as the potential number of jobs that are available per potential worker (viz. Hansen, 1959). I will term these quantities Job Provision Ratios (JPRs).

An important property of this measure is that it allocates every job exactly once (i.e. there are no leftover unallocated jobs) to potential workers in an excludable way (i.e. if a job is allocated to a particular worker, that job is no longer available to other workers) (Shen, 1998, pp. 363-364). Thus, this ratio accounts for both connectivity and competition effects: as the number of jobs within an area’s catchment increases, the ratio for that area will increase, but as the number of potential workers who can reach the same catchment (and thus compete for the same jobs) increases, the ratio will decrease. This property is especially useful for assessing whether the local supply of jobs is sufficient to satisfy the local demand, and methods to assess the degree of inequality in distributions such as Lorenz curves can be straightforwardly applied.

The use of this measure requires two choices. The first choice involves which spatial units to use for the analysis. Some studies divide the study area into a grid of equally-sized squares, in order to minimise distortions in the travel cost calculations due to differences in size and shape between areas (Kotavaara, et al., 2012; Tenkanen, et al., 2016; Järv, et al., 2018; Wang, et al., 2018; Hu & Downs, 2019). However, aggregating data to these squares requires very spatially disaggregated data (which is unlikely to be publicly available) or additional modelling and assumptions to reproject available data to the squares, at the risk of distorting the data. To avoid this, I follow the majority of extant studies (Shen, 1998; Sanchez, 1999; Luo & Wang, 2003; El-Geneidy, et al., 2016; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Deboosere & El-Geneidy, 2018) to divide up my study area into pre-existing spatial units, specifically the 983 Middle-layer Super Output Areas (MSOAs) within the GLA boundary. These are spatial data reporting units created by the UK’s Office of National Statistics that break up the UK’s land mass into areas that contain between 5,000 and 15,000 residents or between 2,000 and 6,000 households, and allow my analysis to directly incorporate a wide range of UK government statistics that are spatially disaggregated to the MSOA level.

The second choice involves how to define the function . Many studies use power or exponential functions so that decreases smoothly as increases (Shen, 1998; Sanchez, 1999; Kotavaara, et al., 2012; Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018; Hu & Downs, 2019). This more accurately reflects the “distance decay” in the attractiveness of destinations that are further away. However, fine-grained origin-destination flow data and additional modelling are needed to estimate the parameters for the distance decay functions, and the resulting raw accessibility values are scores that have no intrinsic meaning and can only be interpreted relative to other scores (El-Geneidy, et al., 2016, p. 304).

In contrast, I will follow Luo & Wang (2003), El-Geneidy et al (2016), Tenkanen et al (2016), Deboosere et al (2018) and Järv et al (2018) to use what Geurs and van Wee (2004) call a “contour” measure, in which:

where X is some travel cost cut-off. This is undoubtedly a distortion of reality, as it treats all locations where as if they were equally attractive and all locations where as if they were totally unattractive. However, the distortion is relatively easy to understand and does not require further assumptions and modelling, and it has the benefit of maintaining the raw accessibility values as simple ratios that can be interpreted directly (Luo & Wang, 2003; Deboosere & El-Geneidy, 2018). At any rate, El-Geneidy et al (2016, p. 303) found that contour and distance decay-based measures are highly correlated and can be used interchangeably. For the purpose of this study, I will set X to 45min, following TfL’s (2018, p. 224) own analyses.

*Inter-MSOA Travel Time Data*

We need a matrix of inter-area travel costs C to calculate R. Most extant studies obtain this by compiling a multimodal transport network dataset, incorporating network link speeds, transport service schedules or assumed service frequencies, implementing a routing algorithm, and then finding the shortest route or routes between every pair of areas and calculating the associated costs. See Ford et al (2015, pp. 129-130) for a step-by-step guide. A significant benefit of this approach is that researchers have full knowledge of the underlying network data and routing assumptions used to generate the travel costs, and can easily simulate alternative scenarios by adjusting the network and recalculating the costs. However, the approach requires an extensive data compilation and cleaning effort and is sensitive to the researchers’ choice of routing algorithm.

An alternative that has become feasible in recent years is to use automated fare collection data in public transport networks to obtain the mean or median travel time between any two stations. This is especially effective for systems where travellers must validate their payment media upon both entrance and exit. However, a general limitation of this approach is that the cost of first- and last-mile travel (from the trip origin to the first entry point into the public transport system, and from the last exit point from the system to the final destination) is not reflected in the data, and more modelling is required to fill in these gaps. Two other factors also limit its applicability in the context of London. First, while TfL’s automated fare collection system captures the locations of travellers upon boarding a bus or entering a rail-based vehicle, the alighting locations of travellers using buses (about 45% of all boardings of TfL vehicles) (Transport for London, 2018, p. 29) are not recorded. While the missing alighting locations can be imputed using modelling to some extent, this may introduce systematic distortions into the data. Second, the raw data is highly protected because it is possible to use it to identify individual travellers in the system, and recent studies using TfL’s automated fare collection data have had to rely on data that is many years out of date (+ citations).

Instead, I obtain inter-MSOA travel data from Transport for London’s (TfL’s) Journey Planner (2019). This is a data service that provides the public with guidance on how to travel between any two points in London by walking, cycling or motorised public transport like buses, trams or trains (but not by car or taxi). This data source has several compelling advantages. First, it allows me to obtain travel cost data without having to build my own transport network dataset for London, and the results reflect the network and routing assumptions actually used by TfL to assist real travellers in London. Secondly, the travel information is door-to-door, covering both first- and last-mile travel and travel within the public transport network. Thirdly, the data is highly disaggregated: besides information on the overall fare, distance and time needed for the trip, the time and distance information is separately reported for each leg of the trip. Finally, the data is freely available in bulk through an Application Processing Interface (API), subject to a limit of 300 trip queries per minute (Transport for London, 2019).

However, using it in this study does impose some constraints on the study design. This is because the Journey Planner provides information only for trips that do not involve cars or taxis, and is most reliable for trips within the GLA boundary. As such, my analysis will concentrate only on areas within the GLA boundary and will exclude travel by car or taxi. Fortunately, TfL data (2018) show that only 37% of trips within the GLA in 2017 used cars or taxis, while 80% of trips within the GLA boundary were by GLA residents. Nonetheless, I recognise that my results will be distorted by the fact that they omit connectivity by car and taxi (and thus will tend to underestimate accessibility levels, particularly in areas with sparser public transport coverage), and do not account for trans-boundary effects (that is, the competition effects of the job and labour pools outside the GLA boundary).

To obtain the inter-MSOA travel time data, I submitted requests for information on trips from each MSOA’s population-weighted centroid to every MSOA’s job-weighted centroid. All requests were for trips ending at 0830 on Friday, 22 March 2019, reflecting trips that take place during the AM peak period on a typical weekday. To ensure that travel times reflect optimal service conditions that are not affected by real-time disruptions, I submitted the requests far in advance of 22 March 2019, over 1 month from January to February 2019.

*Inter-MSOA Travel Time Variability Data*

As the Journey Planner provides travel guidance in real time, I also use it to obtain the travel times for selected origin-destination pairs over different days. The overall distribution of travel times per pair constitutes a measurement of its travel time reliability. However, it is important to note that the travel time distributions obtained through this way probably underestimate the real level of travel time reliability.

Journey Planner travel times incorporate access (the time needed to walk to and from stations or between platforms in stations), waiting and in-vehicle times. Access times are based on assumed walking speeds between and within stations, and do not reflect in-station crowding that may reduce walking speeds around and in stations. On the other hand, waiting and in-vehicle times are calculated solely on service schedules and do not reflect live vehicle locations. In particular, as long as vehicles are running along a route, the Journey Planner assumes all vehicles are running as scheduled, even if they are in fact affected by delays due to breakdowns or en route congestion. Also, the Journey Planner assumes that travellers will always be able to board the first suitable vehicle that arrives, and thus does not reflect the possibility that in-vehicle congestion may prevent boarding.

Finally, the Journey Planner only partially accounts for the impact of service disruptions on routing options. If there are service suspensions (i.e. no services running) on rail routes (National Rail, Underground, Overground, Docklands Light Railway, TfL Rail and tram) due to disruptions or planned shutdowns, the Journey Planner will not return routing options that require travel along the suspended sections. However, if services are just delayed but not completely suspended, the Journey Planner will still continue to recommend routes via the affected services (with an additional alert that service frequencies are affected by delays). Also, it assumes that walking, cycling and bus routes are never suspended. In particular, the Journey Planner will still recommend using a bus service between two stops, even if that service is actually diverted and service to either or both of the stops in question is suspended (if the routing results involve a service that is diverted, an alert describing the extent of the diversion is returned with the results; however, alternative routing options taking the diversion into account are not provided).

As such, the travel time distributions obtained from the Journey Planner only reflect two sources of variability: the need to reroute travel to avoid service suspensions on rail routes, and fluctuations in wait times during transfers between services due to a lack of synchronisation between schedules of different services at different times during the day. While this is a limitation of using the Journey Planner data to capture travel time variability, the two sources of variability captured are relevant in ensuring reliable services. Optimising service schedules is a prerequisite for improving travel time reliability, and the outsize impacts of rail service suspensions on travel times justifies substantial efforts to minimise their occurrence.

To obtain a distribution of travel times per trip during the AM peak on a typical weekday, I requested for travel information on selected trips beginning between 0600 and 0800 over 50 weekdays between 29 January 2019 and 25 April 2019. I found that there was only enough time to process about 7,000 trip requests in the two-hour window in real time, so I only gathered data on trips starting from all 983 MSOAs’ population-weighted centroids that end at the job-weighted centroids of 7 MSOAs that correspond to 7 key transport nodes evenly spaced across the GLA area, totalling 6,881 origin-destination pairs. See Appendix XX for details on how the 7 destinations were selected. I varied the start time of each trip every day by randomising the order in which requests for the 6,881 trips were submitted to the API. This allowed the data to capture the variation in schedule synchronisation between different services for each trip at different points during the weekday AM peak, and the resulting distribution of travel times per trip represents the trip-specific probability distribution of the travel time for any randomly selected start time between 0600 and 0800.

**Results**

*Distribution of Working-Age Residents by Location and Relative Social Deprivation*

Figure XX visualises the distribution of working-age residents (or potential workers) as a dot density map. In general, potential workers are quite evenly distributed across the GLA area. However, a ring pattern can be discerned, with lower residential densities near the centre, higher densities in a ring around the centre, and decreasing densities as one moves away from the centre.

Potential workers living in different areas of London have different sociodemographic characteristics. While the population counts in Figure XX are not disaggregated by characteristics like income, education level or disability status, MSOA-level variations in these characteristics are reflected in the IMD data. Figure XX visualises the ranking of each MSOA by IMD scores, together with 3 raw indicators of social disadvantage, namely the modelled mean household income in 2015 (post-housing costs and equivalised for household size) (+ citation), the estimated proportion of households in poverty in 2014 (+ citation), and the unemployment rate among working-age residents in 2017 (+ citation). For all 4 maps, MSOAs are binned into deciles by their values for each indicator for the purposes of visualisation, with the 10% of MSOAs that are most deprived visualised in dark red and the 10% least deprived MSOAs in dark green. In general, the spatial distribution of IMD rankings corresponds quite well to the distributions of the 3 raw indicators of social disadvantage, with a swath of more deprived MSOAs running north-south along the Lea Valley and another swath running from Dagenham to Clerkenwell along the northern bank of the River Thames, with other significant clusters around Shepherd’s Bush, Elephant & Castle and Streatham. Also, the absolute values of the Spearman rank correlation coefficients between the IMD rankings and each of the other 3 indicators are between 0.8 and 0.9, further confirming that the IMD ranks effectively capture multiple dimensions of social deprivation in London.

*Overall Job Provision Ratios*

Each area’s JPR is a function of 3 components: the spatial distributions of potential workers and jobs, and the connectivity provided by the public transport system. Together with the distribution of potential workers, Figure XX also visualises the job distribution as a dot density map. The distribution of jobs is much more clustered than the population distribution, with extreme concentrations in the centre of the GLA area, where the City of London, Westminster and Southbank are located. However, there are also smaller concentrations of jobs around some stations in the GLA’s rail network (black lines in the figure, including National Rail, Underground, Overground and Docklands Light Railway networks), most notably at Canary Wharf.

The third component, area-to-area connectivity, is captured in the matrix C. Each value of ci,j in C is the minimum time it takes to travel between the population-weighted centroid of MSOA i and the job-weighted centroid of MSOA j to arrive at 0830 on a typical weekday, assuming that all services run as planned. It is difficult to visualise the entire matrix in a meaningful way, but Figure XX visualises the travel times for all trips originating from the most populous MSOA: Stratford, ID E02000726, (i.e. the row vector ), with all areas within 45min travel time from Stratford (i.e. the areas where f(cE02000726,j) = 1) outlined in blue and a dot density map of the distribution of jobs superimposed. In the JPR calculations, each MSOA j within the blue boundary will contribute some of its jobs to each working-age resident in Stratford; exactly how much each MSOA j contributes depends on how many other working-age residents live in areas where they can also reach each MSOA j within 45min.

Figures XX, XX and XX visualise the steps needed to calculate the matrix R containing the JPRs for each MSOA. First, Figure XX shows the number of potential workers who can reach each destination MSOA j within 45min, which is the result of . A dot density map of the distribution of potential workers is superimposed. It is clear that the public transport system heavily emphasises fast connections to the centre of the GLA area, with central areas being within 45min travel time of the most potential workers, and the number of potential workers able to reach each MSOA j declining as one moves away from the centre. Nonetheless, areas near major rail interchanges towards the outskirts may still be reachable within 45min by many potential workers, as they benefit from better rail connectivity by virtue of being en route to the centre from points outside the GLA.

Figure XX shows the number of jobs in each MSOA j that is allocated to each potential worker who can reach it, which is the result of . A dot density map of the distribution of jobs is superimposed. This ratio increases as the number of jobs in each MSOA j increases but decreases as the number of potential workers who can reach it increases. A clear ring pattern can be seen, as in the most centrally located MSOAs, the sheer volume of jobs available offsets the high number of potential workers who can reach them, while a ring of MSOAs around the centre have few jobs but are easily reachable from many areas around London (which spreads the limited jobs available more thinly across larger catchments), and the MSOAs near the outskirts have few jobs but are also relatively isolated from other areas (so that the few jobs available are shared only among small, sparsely populated local catchments).

Finally, Figure XX displays the JPR for each origin MSOA i, which is the sum of all the per-worker job allocations from each MSOA j that can be reached within 45min. This is the result from . In order to interpret whether an MSOA’s JPR is high or low, we need to compare it to an ideal case in which jobs, potential workers and connectivity were all evenly distributed throughout the GLA area, which would result in all MSOAs having JPRs equal to , the ratio of the total number of jobs to the total number of potential workers. This value in the GLA area is 0.88. To express the extent to which each MSOA’s JPR deviates from , JPR values are binned into 5 classes: 0 to 50% of (thus there are far too few jobs allocated to meet the needs of the potential workers), 50% to 80% of (the number of jobs allocated is somewhat insufficient for the number of potential workers), 80% to 125% of (the number of jobs allocated is proportional to the number of potential workers; this is a balanced state), 125% to 200% of (there are not enough potential workers within reach to fill the allocated jobs), and more than 200% of (there are far too few potential workers within reach to fill the allocated jobs). In general, unbalanced JPRs tend to lead to longer commutes, either because workers cannot find enough jobs near them, or because they do not live near where jobs are available.

From Figure XX, we can see how the interaction between unevenly distributed jobs and potential workers on the one hand and uneven connectivity on the other results in most MSOAs in the GLA area having unbalanced JPRs. MSOAs near the centre have much too few potential workers within reach to fill the available jobs, while many MSOAs around the outskirts provide too few jobs per potential worker. A notable exception is the relatively more balanced JPRs in the west, where Heathrow Airport provides a significant number of jobs, and the connectivity between Heathrow and residential areas in the west is relatively good.

Because the JPRs reflect an allocation of jobs among potential workers that treats jobs as excludable, it is straightforward to construct a Lorenz curve for the distribution of jobs among potential workers, by sorting the MSOAs in ascending order by JPRs and then plotting the cumulative proportion of the potential workers against the cumulative proportion of all jobs that are allocated to them. This Lorenz curve is in the inset of Figure XX, and it neatly summarises the inequality in the job allocation: the bottom 50% of potential workers in the more job-poor areas share only roughly 20% of the jobs, while the top 10% of potential workers in the most job-rich areas have their pick of 20% of the jobs.

*Analysis of Job Provision by Sector*

The job distribution data disaggregates jobs by Standard Industrial Classification Codes (SICCs). Thus, we can calculate JPRs by sector and analyse the extent to which job accessibility varies by sector. First, I aggregate the SICCs to 6 overarching sectors:

1. Primary and Extractive
2. Industrial
3. Retail, Logistics, Food & Beverage and Hospitality (hereafter consumer services)
4. Finance, Insurance, Real Estate, Professional and Administrative Support (hereafter high-end services)
5. Public Sector
6. Others

The pie chart in Figure XX shows that 42% of all jobs are from the high-end services sector, while consumer services and the public sector make up another 24% and 22% respectively. Figure XX plots the distribution of jobs in each sector as a dot density map. The spatial distributions of industrial and consumer services jobs are the most decentralised, while public sector jobs are somewhat clustered around some rail interchanges. Unsurprisingly, high-end services jobs are the most concentrated in the centre and at Canary Wharf.

For each MSOA, I recalculate JPR values using the overall potential worker distribution and the job distribution for each sector, and plot maps of the sector-specific JPRs in Figure XX. This set of JPRs represents the number of jobs from each sector allocated to each potential worker per MSOA. The top left panel of Figure XX reproduces the map of the JPRs for all jobs from Figure XX for comparison. Each map uses the same binning scheme as the top left panel, except that the values of are now sector-specific. From the maps, we can see industrial jobs are most evenly allocated across the potential workers, while public sector and consumer services jobs are also relatively evenly allocated albeit with significant over-provision at the centre of the GLA area. In contrast, high-end services jobs are very unevenly allocated, with potential workers living in large swaths of MSOAs in the south, east and north having almost no jobs allocated from this sector, while potential workers living in MSOAs in the centre are allocated between 200% and 360% as many high-end services jobs as the GLA average. The allocation of jobs from the primary & extractive and other sectors is also quite uneven, but there are so few jobs from these sectors in the GLA area that they do not make a significant difference to the overall situation.

When we plot Lorenz curves of the sectoral job allocation to all potential workers (lower right panel of Figure XX), we can assess the extent to which the unevenness of the allocation of jobs in each sector contributes to the unevenness in the overall allocation of jobs. The Lorenz curves for the industrial, consumer services and public sectors are closer to the diagonal than the curve for all jobs, but the curves for the primary & extractive, high-end services and other sectors are below the curve for all jobs. This indicates that the distributions of jobs in the latter three sectors tends to make overall job allocations more uneven in the GLA area. In particular, because the high-end services sector is the largest in the GLA, the high concentration of jobs in this sector in the centre of the GLA area tends to drive the unevenness in accessibility to jobs in the GLA area.

Finally, because JPRs allocate jobs in an excludable way, we can decompose each MSOA’s JPR sectorally and analyse the proportion of each MSOA’s overall JPR that is contributed by each sector. This indicates the extent to which each MSOA is dependent on each sector for its job allocation. Figure XX visualises these sectoral dependence proportions, with the MSOAs binned into quintiles for visualisation in each map. Firstly, it is clear that jobs in the primary & extractive and others sectors never make up a significant proportion of any MSOA’s job allocation. Secondly, areas near the outskirts in the northwest, north and east are especially reliant on industrial jobs, areas near the outskirts in the north, east and west (particularly around Heathrow) are unusually reliant on consumer services jobs, and two swaths along the northern boundary of the GLA area and south of the Thames are particularly reliant on public sector jobs. Finally, the most centrally located areas are disproportionately reliant on the high-end services sector.

*Analysis of Variability in Travel Times*

For each of 6,881 origin-destination pairs, I obtained a distribution of 50 minimum travel times over 50 days. From this data, I then calculate the RBT for each origin-destination pair. Recall that the RBT is the difference between the 95th percentile and median travel times for a trip, and reflects the extra time that a traveller needs to budget for in order to be 95% confident that she will not arrive late.

Each panel in Figure XX plots the RBTs of trips originating in each MSOA and terminating at one of the 7 destinations (outlined in red in each map). To facilitate comparison of RBTs across all origin-destination pairs, all maps use the same binning scheme to visualise the RBTs, with green shades indicating lower RBTs that are under 10min. In general, we can see that areas that are directly connected to the destination by rail tend to have lower RBTs, as trips from these areas do not involve interchanges, so travel times are only affected by service schedules. Areas that are not directly connected to a destination by rail tend to have higher RBTs, even if they are relatively near the destination. Trips from such areas tend to require more interchanging, particularly if bus travel is needed, and this increases the probability of increased waiting times due to a lack of schedule synchronisation between different services. Also, trips originating from locations further from a destination tend to have higher RBTs, as these trips tend to involve more interchanging too, and long-distance travel tends to rely more on rail-based modes and are thus more vulnerable to service suspensions.

Also, we can see that trips ending in destinations north of the Thames, particularly in the City but also in Finsbury Park, Harrow-on-the-Hill and Hammersmith, tend to have lower RBTs. This may be due to the more grid-like rail network north of the Thames, which provides commuters with more alternative rail routes if service on a particular section of the rail network is suspended. In contrast, travel times to Lewisham and Streatham tend to be less reliable. This probably reflects two factors: the more tree-like structure of the rail network there (which provides less network resilience against failures along the rail lines leading to these destinations) and reliance on National Rail services to reach these two destinations (these services tend to run less frequently than TfL’s rail-based services, thus increasing the likelihood of increased waiting times during interchanging because of schedule desynchronisation). Finally, for all destinations, we can see that trips originating from the southeastern quadrant of the GLA area tend to higher RBTs. This probably reflects the effects of the less frequent and less reliable rail services run by Southeastern and Southern Railways (+ citation).

*Contributions to Travel Time Variability by Travel Mode*

As we have seen, the level of travel time reliability differs across trips. But why do some trips have less reliable travel times than others? Four factors have already been mentioned: the distance covered for each trip, (as reliance on rail-based modes and the probability that a disruption will affect the trip probably increases with trip distance), the number of interchanges (which increases the probability of increased wait times due to schedule desynchronisation), the reliability of different travel modes (TfL rail-based services seem to be more reliable than the bus), and location-specific factors (like the extent to which the local network is gridlike rather than treelike, or the reliability of the operators that serve an area).

To investigate how these factors shape travel time reliability across trips, I carry out a set of linear regression analyses with trip-level RBTs as the dependent variable. The initial model I fit is:

where:

* Y is a n x 1 column vector where yi is the RBT for trip i;
* T is a n x 1 column vector where ti is the number of interchanges (that is, the number of non-walking legs minus 1) needed for trip i assuming the trip ends at 0830 on a typical weekday and that all services run as scheduled;
* D is a n x m matrix where m is the number of travel modes and di,k is the total distance covered by mode k for trip i assuming the trip ends at 0830 on a typical weekday and that all services run as scheduled;
* α is an intercept term, β is a scalar representing the partial effect of transfers on RBT, γ is a m x 1 column vector representing the partial effects of distance covered by each mode on RBT, and ε is an idiosyncratic disturbance.

With this model, I investigate how the characteristics of a trip assuming that it ends at 0830 and that all services run as scheduled are correlated with the reliability of travel times for that trip for travel during the AM peak.

The results for this model are shown in Column 1 of Table XX. They indicate that every additional transfer during the trip adds about 0.5min to the RBT. In addition, every additional kilometre travelled by bus or National Rail increases the RBT by 0.4min and 0.06min respectively, indicating that travel by these modes tends to reduce travel time reliability. Although the Journey Planner data do not reflect the effects of congestion and diversions on travel times by bus, bus travel tends to involve more interchanging, and frequencies on bus services tend to be lower than on TfL-operated rail-based services, which increases the risk of schedule desynchronisation during interchanges to bus services. The result for National Rail is consistent with the fact that National Rail services are less frequent and more prone to service suspensions than TfL rail-based services. On the other hand, travel by Underground, tram and Docklands Light Railway tends to reduce RBTs.

Because all the MSOAs are connected to each other via the same transport network, there is likely to be a mutual correlation structure between the RBTs of different trips. For instance, two MSOAs that are located along the same rail line can be expected to have similar RBTs for trips via that line, as both will be affected by any disruptions along that line. If the non-independence of the RBTs between trips is not accounted for, the correlation structures among different RBT observations may distort the coefficient estimates for the covariates included in the model.

One way to deal with such correlations is to use a spatially autoregressive model, in which the value of the dependent variable in each area depends on the mean of the value of the dependent variable in its neighbours. This captures the idea that areas that are near each other tend to be similarly connected to the larger network of areas and thus should experience similar network-related effects. To implement this, I first obtain for each MSOA a vector of travel times to the 7 destinations from the baseline data, and then calculated the Euclidean distance between every pair of vectors. Then, for each MSOA, I identify the 3 other MSOAs where this Euclidean distance is minimised; these are the MSOAs whose travel times to the 7 destinations are the most similar to those of the MSOA in question, assuming all services run as scheduled. Then, for each trip originating from the MSOA in question and terminating at each of the 7 destinations, I calculate the mean RBT for trips starting from the 3 neighbours and ending at the same destination. For an illustration of where the 3 neighbours are located for the case of Stratford, see Figure XX.

Figure XX displays the RBT and corresponding local mean RBT among the 3 nearest neighbours for each of the 6,881 origin-destination pairs. There is significant correlation between the two. I then fit the following model:

where L is a n x 1 column vector where li is the local mean RBT for trip i, and δ is a scalar representing the partial effect of local mean RBTs on the RBT.

Column 2 in Table XX presents the results for this model. As expected, the local mean RBT allows the model to better capture the correlation between the RBTs of MSOAs that arise due to their locations in the transport network. Specifically, as the local mean RBT increases by one minute, the RBT of the MSOA in question tends to increase by 0.5min. The inclusion of the local mean also reduces the confounding of the estimated coefficients for the other covariates due to network effects, reducing the magnitude of the estimates by about 40% for the number of transfers, 35% for bus and 55% for National Rail. However, the coefficients still indicate that bus travel contributes the most to travel time unreliability, followed by National Rail, and that travel by Underground, tram and Docklands Light Railway tend to increase travel time reliability.

While the previous two regression models generate one global estimate for the partial effect of distance travelled by each mode and the RBT of a trip, we have seen signs that the mode-specific effect may vary across locations (recall that National Rail services seem to contribute particularly significantly to travel time unreliability in trips from the southeast). To investigate this, I use locally-weighted regression, which uses only the trips originating from the closest neighbours for each MSOA and ending in the 7 destinations to fit a linear regression model to generate one estimate for each coefficient for each MSOA. I define as neighbours the 30 MSOAs whose travel times to the 7 destinations are most similar to those of the MSOA in question (using the same Euclidean distance calculation as the derivation of the local mean interval width). Figure XX illustrates for Stratford, which MSOAs are included in the locally-weighted regression and which are further considered for calculating the local mean of the interval width. As the travel time vectors for each MSOA are unique, the local regression for each MSOA is very likely to use a subset of local neighbours that is unique to that MSOA, and this will thus yield a vector of coefficient estimates that is unique to each MSOA.

First, we examine some diagnostics of the locally weighted regression implementation. Figure XX maps out the adjusted R2 values for the locally fitted regression models. The median local adjusted R2 is 0.23, similar to the adjusted R2 of the model in Column 2 of Table XX, but the local adjusted R2 can vary from as low as 0.05 in the outskirts to 0.69 around Westminster. The local adjusted R2 tends to be higher near the centre where the rail network is densest, but is quite low towards the outskirts, particularly south of the Thames; this indicates that travel time variability in the outskirts is less correlated with the characteristics of the fastest travel option assuming all services run as planned than with other factors that have not been included in the model (such as the frequencies of services at nearby stations or the distance covered by services under each operator). Next, Figure XX maps out the p-values for each coefficient estimate for each MSOA. Dark blue areas are where the coefficient estimates obtained were not statistically significantly different from 0. Grey areas are where p-values are missing; this indicates that there was no estimate for the coefficient for that MSOA, because there was no variation in that covariate among the MSOAs considered in the local regression.

Column 3 in Table XX displays a summary of the distributions of the coefficient estimates for each covariate obtained from the locally weighted regression. The distributions of local estimates contain the global estimates from Column 2, but capture the variation in each coefficient across space. Figure XX maps out the coefficient estimates for each covariate and each MSOA. Green (red) shades indicate that the covariate tends to increase (decrease) travel time reliability in that MSOA. Grey MSOAs indicate where the coefficient estimates were not statistically significantly different from 0 or were not available.

At the local level, increasing travel by bus tends to decrease travel time reliability almost everywhere in London, but particularly in the northeast around Stratford, Barking and Leytonstone, around the City, Westminster, Rotherhithe, Lewisham, Sidcup and in a swath from Waterloo to Wimbledon. Travel by National Rail degrades travel time reliability in a large swath in the southeast, indicating further evidence of operational unreliability by Southern and Southeastern Railways. In fact, National Rail services in these areas seem to be so bad that increasing the number of interchanges and increasing travel by bus and walking (and thus reducing reliance on National Rail) tend to improve travel time reliability, contrary to patterns elsewhere. However, travel by National Rail also reduces travel time reliability in a northwestern corridor from Paddington to Ruislip, and around Stratford. This could reflect how National Rail lines north of the Thames tend to terminate outside the City (in stations like Paddington, Marylebone, Euston, Kings Cross, St. Pancras and Liverpool Street) and provide poor orbital connections, so National Rail users need to interchange more to complete their journeys to one of the 7 destinations. On the other hand, the local effects of travel by Underground, tram, Overground and Docklands Light Railway on travel time reliability tend to be positive or not statistically significant. Travel by the new TfL Rail service tends to reduce travel time reliability, particularly in the west; this may be because TfL Rail operates on tracks that are also used by National Rail services, and thus may also be more vulnerable to the reliability issues of National Rail.

*Typology of London MSOAs by JPR, Sectoral Dependence for Job Allocation, Travel Time Reliability and Mode-Specific Contributions to Reliability*

As we have seen above, there are uneven spatial distributions for JPRs, sectoral dependence for jobs, travel time reliability and mode-specific contributions to travel time reliability. In addition, we know that working-age residents living in different areas of London have different levels of social deprivation. It is possible to develop a typology of MSOAs in the GLA area to examine how these dimensions intersect with each other, to develop a more nuanced understanding of job accessibility and more precisely diagnose problem areas that may warrant additional interventions.

I carry out a k-means clustering analysis using 9 dimensions:

* Overall JPRs, to capture overall job accessibility
* The percent of each MSOA’s JPR contributed by high-end services, to capture sectoral dependence for job allocations, since we have seen that the high-end services sector is the largest single sector in the GLA area and it tends to make the job allocation more uneven
* The RBT for travel from each MSOA to the City, to capture travel time reliability to the most job-rich area in London
* I also identify which of the 6 other destinations are closest to each MSOA assuming all services run as planned, and then include the RBT for travel from each MSOA to its respective closest destination. In the absence of travel time distributions for every origin-destination pair, this RBT can represent to some extent the reliability of travel times from each MSOA to its immediate neighbourhood.
* MSOA-level coefficients for distance travelled by bus, Underground, National Rail and walking from the locally weighted regression, to capture mode-specific effects on travel time reliability. Coefficients for other modes are not included because MSOA-level estimates for those coefficients are missing for some MSOAs.
* The IMD rank for each MSOA, to capture the sociodemographic characteristics of the working-age population.

The results for a clustering with 8 clusters is shown in Figure XX. By social deprivation, three types of clusters are apparent: Clusters 0, 1 and 2 tend to contain MSOAs with lower deprivation, Clusters 5, 6 and 7 tend to contain MSOAs with higher deprivation, and Clusters 3 and 4 are more diverse.

Cluster 3 (with about 8% of the working-age population) contains the most centrally located MSOAs in the City, Westminster and Southbank. As these areas are the most job-rich, MSOAs in Cluster 3 are distinguished by having the highest JPRs, indication extreme surpluses of jobs allocated per potential worker. They are also among the most dependent on the high-end services sector for jobs. Their central location gives them access to many public transport routes, especially rail-based routes, resulting in extremely reliable travel times to the City and to their local destinations. Reliability of travel by mode tends to be average, except for travel by National Rail, which seems to be less reliable. This could be due to scheduling desynchronisation between services by National Rail and other modes. In contrast, the MSOAs in Cluster 4 are distinguished by their combination of job poverty and high travel time unreliability, especially to the City. This unreliability is disproportionately due to the unreliability of National Rail services in the southeast, so much so that trips that involve more distance covered by bus, walking or Underground (and thus rely less on National Rail) tend to be more reliable. Fortunately, only about 2% of potential workers live in MSOAs in Cluster 4.

Of the three least socially deprived clusters, Cluster 0 (with 15% of the working-age population mostly located in the southwest in areas like Richmond, Kingston, Wimbledon and Battersea) tends to have the most balanced JPRs, indicating sufficient jobs allocated per potential worker. These potential workers tend to rely more on high-end services for their job allocations, but because of their low social disadvantage, they may be more likely to have the skills and resources to take advantage of jobs in this sector. Travel times to the City and to local destinations tend to be quite reliable, and indeed this area seems to enjoy the most reliable Underground and National Rail services in London. MSOAs in Cluster 1 (with 23% of the working-age population and covering areas near the outskirts) also enjoy relatively reliable travel times to the City and local destinations, but experience job shortages due to their greater distance from the centre and the scarcity of jobs in the outskirts. In contrast, MSOAs in Cluster 2 (with 10% of the working-age population located near the outskirts) experience both insufficient jobs and high travel time unreliability, particularly due to National Rail services.

The situations facing the most socially deprived clusters are also nuanced. MSOAs in Cluster 5 (with 18% of the working-age population) are located quite centrally, almost surrounding the MSOAs in Cluster 3. As a result, MSOAs in Cluster 5 enjoy similar conditions as Cluster 3, benefitting from excellent transport connectivity, high travel time reliability and a surplus of jobs allocated per potential worker. However, these jobs also tend to be from the high-end services sector, which more socially disadvantaged workers (who may lack educational qualifications, relevant working experience or social networks) may find more difficult to take advantage of. Of course, the high-end services sector does contain some jobs suitable for workers from less privileged backgrounds, but the degree to which the sheer volume of jobs available can compensate for the tendency for skills mismatch between high-end services jobs and more socially disadvantaged workers is unclear from this analysis.

MSOAs in Cluster 5 (containing 18% of the working-age population) are located further towards the outskirts, especially in the Lea Valley in the north, areas from Ealing to Hayes & Harlington along the TfL Rail line in the west, areas along the Overground line from Brockley to Croydon in the south, and Becontree and Dagenham in the east. They are characterised by relatively reliable travel times but a lack of jobs. Travel seems to be reliable but too slow to connect these areas effectively to large job clusters. In contrast, MSOAs in Cluster 6 (containing 18% of the working-age population in Stratford, Ilford, Barking, the Royal Docks and Greenwich) have relatively balanced JPRs and reliable travel times to the City, but less reliable travel times to local destinations. The reliability of buses and National Rail in these areas seems especially problematic. These areas are also more dependent on the high-end services sector for jobs. Thus, skills mismatch between potential workers and the available jobs may be more likely to arise in these areas.

In summary, the k-means clustering analysis allows us to develop a typology of MSOAs in the GLA area that captures a more nuanced understanding of job accessibility, allowing us to expand on the usual focus on job-worker spatio-temporal matching to also consider sectoral dependency for job allocations, travel time reliability and worker sociodemographic characteristics. This analysis reveals that besides simply having to many or too few jobs allocated to each potential worker within a reasonable travel time, each area may also face challenges in terms of skills mismatch and travel time reliability, especially by bus or National Rail. The particular combination of challenges in each area suggests that intervention strategies should be tailored to each area’s characteristics.

**Discussion**

*Results in the Context of Extant Literature*

The analysis of job accessibility in the GLA area, as captured by the MSOA-level JPRs, indicate that job accessibility is unevenly distributed across space, with locations nearer the centre and near major public transport network nodes having more jobs allocated per potential worker, and locations towards the outskirts and with poorer connections to the public transport network having too few jobs per potential worker. Though they may use different location-based accessibility measures, other studies of Boston (Shen, 1998), Montreal (El-Geneidy, et al., 2016), Santiago (Neihaus, et al., 2016), Bogota (Guzman, et al., 2017; Guzman & Oviedo, 2018) and 11 major Canadian cities (Deboosere & El-Geneidy, 2018) also found similar patterns where job accessibility is highest where the public transport network is densest. This is an unsurprising finding, as the distributions of housing, jobs and connectivity in cities are all uneven.

The analysis of each MSOA’s sectoral dependency for its job allocation gives some insight into how accessibility varies by job characteristics. In particular, more central areas are more dependent on high-end services for jobs, while areas nearer the outskirts are less dependent on any single sector. Sectoral breakdowns of job accessibility are rare in the literature. However, Shen (1998, p. 355) found that accessibility to jobs in manufacturing, administrative support, sales, services and agricultural sectors for low-income workers by car and public transport in Boston in 1990 was highest in the city centre. This contrasts with my findings, but the discrepancy may be accounted for by the structural differences in the transport networks of the two cities, where Boston’s public transport system is less extensive than London’s, and Boston’s road networks are more effective than London’s at providing fast connections to the city centre from the outskirts. It may also be accounted for by 3 decades of deindustrialisation and specialisation in central business districts, where high-end services firms have increasingly priced out firms in other sectors from the most central locations.

The measurements of travel time reliability for the 6,881 origin-destination pairs confirm the findings from Uniman (+ citation) and Ehrlich (+ citation) that travel times in the public transport network can be quite variable, even if the system operates entirely as planned. However, my RBT estimates seem lower than those previously found. For example, Uniman (+ citation) reports that a trip from Waterloo to Canary Wharf in 2007 had an RBT of 9min. While I did not collect travel time variability data for trips ending at Canary Wharf, the RBTs I measured for trips from Waterloo to Lewisham or Ilford (the two destinations with measurements that are closest to Canary Wharf) are 4min and 1min respectively. Also, Ehrlich (+ citation) found that RBTs for direct bus trips between stops (i.e. that involve only in-vehicle time with no interchanges) varied between 5min and 42min, whereas the RBTs I calculate for all trips (including trips that involve interchanges) range from 0min to 41min. This is understandable, as the data I use to measure travel times in real time do not account for all sources of travel time variability. Nonetheless, my results still indicate that travel times by bus are significantly less reliable than travel times by rail-based modes. This is in line with findings from Uniman (+ citation), Ehrlich (+ citation) and Duran-Hormazabal & Tirachini (+ citation).

The k-means clustering analysis indicates that there are locations in the GLA area where more socially disadvantaged working-age residents suffer from a combination of insufficient accessibility to jobs, dependence on the high-end sector for jobs and/or travel time unreliability. But there are also areas where socially disadvantaged workers benefit from high job accessibility and travel time reliability. This is similar to El-Geneidy et al’s (2016) and Deboosere & El-Geneidy’s (2018) findings in Canadian cities that indicate that low-income workers tend to have good accessibility to jobs that are suitable for them, although problem areas where social disadvantage coincides with low accessibility exist. In contrast, studies of South American cities (Neihaus, et al., 2016; Guzman, et al., 2017; Guzman & Oviedo, 2018) found that there is a systematic tendency for low-income workers to live in less accessible areas; this is probably due to their lack of affordable housing near job-rich centres and less extensive public transport systems.

*Limitations and Further Research*

Overall, the new findings from this study on job accessibility in London seem plausible in the context of the literature. However, we need to keep in mind some caveats when interpreting these result. I list three particularly important ones below, as well as preliminary ideas on how to design future research to better address them.

Firstly, the RBT measurements in this study probably underestimate the true level of travel time unreliability, because it is based on Journey Planner travel time estimates that do not account for real-time vehicle locations and congestion effects on travel time. To a certain extent, this can be addressed using data from other TfL API endpoints, especially for live arrival times at stops. For example, once the fastest route for a trip is obtained from the Journey Planner, the stations where a traveller needs to board and alight can be identified, and separate scripts can then repeatedly request the live arrivals for each station to track the vehicles that the traveller would have ridden on. Actual waiting and in-vehicle times for each leg of the trip can then be calculated and updated into the database of trip characteristics. Nonetheless, without live vehicle loading data, we would still be unable to account for the effects of in-station and in-vehicle crowding that may reduce in-station walking speeds and prevent boarding of vehicles. In effect, this would be equivalent to tracking the progress of 6,881 ghost travellers (who can occupy the same space as other real travellers) through the system in real time.

Another alternative is to use data from other trip planning applications that do take into account real-time vehicle locations, such as CityMapper. CityMapper data has the added advantage of taking into account bus diversions when suggesting routing options for a trip. However, special permission is required to access CityMapper data in bulk through their API.

Secondly, there may be concerns that the travel time for a trip that ends at 0830 on 22 March 2019 may not reflect the typical travel time for that trip during a weekday AM peak, assuming all services run as scheduled. This is because these travel times are also affected by schedule desynchronisation; for example, a trip that uses an express train may take a shorter time, but the express service schedules may only allow a traveller to reach the destination by 0840. If we plot for each of the 6,881 trips the travel time for a trip that ends at 0830 on 22 March 2019 against the median observed travel time (Figure XX), we do see that there are instances where the real median travel time is markedly more or less than the baseline travel time. However, we also see that the two quantities are highly correlated, with a Pearson correlation coefficient of 0.987. As such, I believe that inaccuracies in the baseline travel time will only marginally affect the job accessibility calculations. However, if it is important to ensure that the baseline times are truly representative of all the possible travel times for a trip, then the best way would be to collect real-time observations of travel times for that trip to construct the travel time probability distribution.

A third limitation is that although my analysis incorporates travel time variability as additional dimensions in the k-means clustering analysis to develop a typology of MSOAs, the JPR calculations for overall job accessibility is no different from those in the extant literature in using point estimates for each of the components that do not capture the stochastic distributions of possible values around the point estimates. One way to address this is to use the 95th percentile travel times instead of the representative travel times in the travel cost matrix C. The resulting JPRs would reflect a job allocation per potential worker from within a reduced catchment that reflects the area within which each potential worker has at least a 95% chance of arriving on time. The key constraint faced by this approach is the API call limit, which makes it possible to gather data on only 7% of all possible origin-destination pairs in real time. A researcher could try negotiating directly with TfL for a more generous call limit for her API account, though this could reduce the API’s availability to serve its intended customers, which are real travellers in London. Another alternative could be to develop a model that is trained on the 7% of pairs with observed RBTs to predict the RBTs for the unobserved pairs. The R2 values for the regression models fitted in this study can give an indication of the promise in this approach; however, I believe that data beyond what the TfL Journey Planner provides (such as information on local network topology) will be needed to improve the model fit to a level where a researcher could be comfortable to rely on its predictions.

*Recommendations for Urban Developments in the GLA*

One of the aims of this study is to obtain findings that can aid in developing multifaceted strategies to improve accessibility to suitable jobs in London, drawing on options from land use development, transport infrastructure and operations and economic and social policy. Below, I list some ways in which the findings discussed above can aid policy-making in these fields.

Firstly, the map of overall JPRs in Figure XX reveals locations where there are too few or too many jobs allocated per potential worker. This can directly guide the distribution of future growth to shape the overall urban structure, with new housing supply being directed to locations with job surpluses, and job growth being encouraged in areas with too few jobs per potential worker. Transport connectivity between areas with high JPRs and low JPRs can also be enhanced, to put more potential workers in job-poor areas within reach of areas with job surpluses. This may be especially effective where adjacent areas have very different JPRs.

Secondly, even though the measurement of travel time reliability in this study probably overestimates actual travel time reliability, the results are still useful for identifying areas where travel times to important destinations like the City are relatively unreliable. The mode-specific reliability analysis also indicates areas where services by different modes seem to be particularly unreliable. Moreover, because the only two sources of travel time variability captured in this study are service suspensions and schedule desynchronisation, the findings from this study can directly justify efforts to adjust service schedules or increasing service frequencies to reduce the probability of schedule desynchronisation during interchanges, or to adjust the incentives for operators so that they put more effort into maintaining services on schedule. Of course, we still need to keep in mind that in some areas, crowding and network topology (in particular the availability of alternative routes) may contribute more to travel time unreliability.

Thirdly, the typologies of MSOAs derived from the K-means clustering analysis can be used to target social and economic policies to reduce the potential for skills mismatch between potential workers and the available jobs. For instance, referring to Figure XX, the potential workers of MSOAs in Clusters 5 and 7 may especially benefit from skills training programmes, which can help bridge the gaps between their relatively high social deprivation and dependence on high-end services jobs. Economic incentives or development strategies to encourage job growth in other sectors, especially consumer services and the public sector, can also be targeted to MSOAs in these clusters.

Finally, the MSOA typology can also be used to prioritise interventions to benefit the most socially deprived areas first, especially since more socially deprived residents may have fewer resources to improve the accessibility situations that they face by themselves, and may have fewer options for travel besides public transport. In order to deliver results quickly, we should look for low-cost and easily implementable interventions that make the most out of existing resources and programmes, such as extending the bus lane network or working with local universities to expand skills training.

To a certain extent, these recommendations are in line with what the GLA already plans to do to improve transport connectivity and distribute growth more equitably throughout London. For instance, the upcoming Elizabeth Line is expected to place many more workers in the east and west of London within 45min travel time of the job-rich centre, and this should help to move the JPRs in areas along the route towards a more balanced state. The Elizabeth Line may be particularly important in improving job accessibility for areas in Ilford and Chadwell Heath in the east, where a shortage of jobs coincides with higher social deprivation.

A similar effect can be expected from the proposed Crossrail 2 project, which runs from the north through the socially deprived and job-poor Lea Valley to the southwest (+ citation). The Mayor’s Transport Strategy (Greater London Authority, 2018) also calls for improvements to bus connectivity and reliability (pp.155-9), improvements to rail reliability south of the Thames (particularly through the conversion of National Rail services to Overground services through “metroisation”) (pp.180-1), and the encouragement of housing and job growth in areas with good connections by public transport (p.214). The findings from this study can add further justifications for pursuing these strategies.

Nonetheless, the findings can aid in prioritising areas for the implementation of these strategies. For instance, the leg of Crossrail 2 that runs north of the Thames benefits more deprived areas than the southern leg, so we should consider building the northern leg first. Also, the Transport Strategy (2018) recommends encouraging job growth in four strategic transport interchanges, Lewisham, Stratford, Clapham Junction and Willesden Junction, to put more jobs within easy reach of workers. This is a sensible strategy, as these four locations are surrounded by areas with low JPRs (from Figure XX). However, Figure XX also shows that the number of working-age residents that can reach Lewisham within 45min travel is relatively low, and the RBTs for travel to Lewisham (shown in Figure XX) are quite high; this indicates that travel speeds and reliability to Lewisham should be improved in tandem with the delivery of more jobs there. This strategy of dovetailing transport improvements and development is probably applicable to the other 3 locations as well, though RBT measurements for trips to those destinations are not available from this study.

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