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A job accessibility index to evaluate employment impacts in isolated regions now restored to the rail network.

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Abstract

Restoration of rail links to rural or isolated regions may generate wider economic impacts by improving employment accessibility. An applicable simplified index is developed based on potential job opportunities, measuring location advantage with respect to the job market. A gravity-based approach assesses the accessibility of the workforce in each location to opportunities in all other locations, where fewer or more distant opportunities provide diminishing influence. Specific issues are the practicability of commuting due to infrequency of public transport to a limited range of destinations, and the types of job available at each location. Consequently, to reflect these effects in a more remote context, measures representing proximity and service frequency were incorporated into the index, with allowance for skills matching with a new approach in closer matching of occupations between different locations. Comparing the accessibility index by location over the intervention period highlighted those areas most impacted by infrastructure changes. Applying the rail intervention of the Stirling-Alloa line as a case study illustrated that not accounting for local job skills matching tends to overestimate the attraction factor of job opportunities, and the wider difference when the job index is based on generalised cost suggests that generalised cost of travel including the value of time is more of an impediment than actual travelling time.

Keywords

rail intervention; isolated regions; employment; job accessibility; skills matching; gravity-based

Word count 7974 (without References)

Introduction

Restoration of rail links to previously disconnected or isolated regions may improve accessibility to jobs, generating wider economic and social impacts. Travel time to employment has been found significant in house location choice, and employment considered the most likely single destination for an accessibility measure. Movements in job accessibility levels can reflect how infrastructure changes impact on commuting and the promotion of social equality.

The aim and focus of this paper is to outline the development of a simplified index of job accessibility that will apply to regions subject to recent restoration of rail links. It will show how the index was calibrated using the case study of the Stirling-Alloa Line as representing a typical rural or isolated example. It will also determine whether this accessibility measure could be used to indicate wider economic impacts caused by the rail intervention.

By assessing the accessibility of the workforce in each location to opportunities in all other locations, it makes comparison by location over the intervention period to highlight areas most impacted by infrastructure changes. It also addresses specific issues relating to remote or disconnected regions, including the practicability of commuting due to infrequency of public transport to a limited range of destinations, and the limited employment opportunities available at each location especially when considering matching skills with available jobs.

This paper focuses on accessibility to job opportunities through development of an index based on job proximity and potential employment opportunities, measuring workforce location advantage with respect to the job market. A gravity-based modelling approach estimates differences in job access for places and people, and assesses the accessibility of the workforce resident in an origin location to job opportunities in all potential destination locations, in which fewer and more distant opportunities provide diminishing influence.

The measure combines an attraction factor and a separation factor, by applying an impedance function where job opportunities are allocated weights inversely correlated to proximity to the jobs. Those areas most impacted by infrastructure changes have been determined by comparing the accessibility index for each location over a period spanning the intervention.

A specific issue relating to rural or previously disconnected areas is the practicability of commuting due to the infrequency of public transport services, and the limited number of destinations served. Also important is the pool of job occupations available at each location. Consequently, the contribution of this paper is specifically in introducing an accessibility measure suitable to this context, building on the existing literature by incorporating measures representing proximity and frequency of services, whilst including an allowance for skills mismatch and other barriers to job accessibility.

Literature Review

The correlation between public transport accessibility and job opportunities has attracted researchers' attention in the literature (Saif et al., 2018) with the focus generally on ex ante or ex post evaluations of the implications for accessibility of policy plans (Van Wee, 2016).

Employment is thought the most likely single destination type for an accessibility measure since commuting is probably the most regular form of travel (Horner and Mefford, 2005). Job accessibility has been defined as the 'potential of job opportunities for interaction' (Hansen, 1959), or the 'ease of reaching work places' (Cervero et al., 1997), and one of the most important tasks of any transport system is to connect workers to jobs (Grengs, 2010).

In defining sustainable accessibility, Bertolini et al (2005) highlighted ‘‘the amount and diversity of places that can be reached within a given travel time and/or cost’’. As a system, job accessibility encompasses transport, jobs and workers or residences (Cheng and & Bertolini, 2013).

In measuring longitudinal shifts in job accessibility, Cervero et al., (1998) suggested two approaches commonly used to measure accessibility: gravity-based measures and isochronic measures. Gravity-based measurement was typically used in representing job accessibility where spatial barriers are taken into account (Reggiani et al., 2011). These were represented by a decay measure or impedance function (Allard and & Danziger, 2002; Cervero et al. (1998); Sanchez et al., 2004), with an attraction measure reflecting the "opportunities" or jobs available. By combining the attraction and decay functions together, the index is weighted to be inversely correlated with proximity.

Gravity models are still widely used and recently Persyn and Torfs (2015) used a gravity equation for commuting to identify the effect of regional borders on commuting and showed that regional borders exert a sizeable residual deterrent effect on commuting with obvious implications for regional labour market integration. This frontier effect differs significantly between regions and depends on the direction in which the border is crossed. Other recent examples include the study of tourism where using panel data, distance and income were found to be major determinants and high urbanization rates in countries of origin are associated with larger flows of incoming tourists (Santoramo and Morelli, 2015).

Although gravity models provide an accurate estimate for comparing job accessibility, they are less intuitive for interpretation. Furthermore, the calibration of a distance decay function and parameter (distance friction) has proved difficult as historical or empirical travel survey data (e.g. commuting matrix) are needed (Reggiani et al., 2011). More recently, accessibility models now include location-based competition where there is a mismatch in the spatial distribution of population and opportunities with capacity constraints (Guers et al., 2015).

Even were a job reachable, it may not necessarily be suitable for every worker, since individual characteristics determine the actual matching of jobs and workers. Job availability for a zone equals the pool of jobs within a subset that is reachable according to the proximity measure. This makes the implicit assumption that any job of a given socio-economic status (Korsu & Wenglenski, 2010) is potentially identically available to any worker of the same socio-economic status. Cervero et al. (1997) introduced ‘match’ into the measurement of job accessibility, where only matched jobs can be taken by specific groups of workers. Workers and jobs should be segmented according to classification, and diversity accounted for in measuring job accessibility. However, little measurement of job accessibility has appropriately incorporated this diversity element and the method of matching did not lend itself to adequately reflect the closeness of the match.

Accessibility to reachable jobs available to any worker will depend on the number of competitors claiming to form a match (Kawabata & Shen, 2007). They identified the reachable and available jobs for any worker resident in a zone and measure the number of actual labour market competitors for each job. Then, job accessibility is defined as the ratio of weighted reachable jobs to the number of labour market competitors for these jobs. Sanchez et al. (2004) developed a gravity-based accessibility model, incorporating competition effects as well as the distance decay effect using a negative exponential function to represent the travel friction effect.

Bunel and Tovar (2013) argue that different local job accessibility models can lead to significantly different empirical depictions of job accessibility. The empirical differences are spatially differentiated, and they found that failing to account for job availability may overestimate job accessibility levels of poorer areas. They developed an appropriate index to estimate these elements in the context of regions restored to the rail network. However they only addressed a specific urban context, the Paris region and were unsure whether the relative importance of the methodological issues was robust in other contexts.

Although covering similar ground to some of the existing literature, particularly in the different aspects an accessibility measure could feature, this paper departs from the existing literature in particularly addressing remote and disconnected regions and is the only approach that encompasses them all in this specific context. Indeed as cities currently benefit to the detriment of rural and semi-rural areas with declining and ageing populations (Glaeser, 2012), the complexity of urban–rural interactions is thought a research area meriting more attention in the light of accessibility issues (Taylor & Susilawati, 2012). Östh et al. (2015) show that economic resilience varies strongly between urban and rural areas where the latter suffer poor accessibility and in general also experience population loss. Caschilli et al. (2014) in showing the interplay between accessibility and rurality in Sardinia find that there is not always a spatial correlation between accessibility and rural nature of an area.

Methodology

Overview

After considering the advantages and disadvantages of various approaches proposed in the current literature, a gravity based index was developed to measure changes in access to employment across different travel modes, in particular, bus, car and rail. The methodology combined and developed various approaches from the current literature, and a job accessibility index was derived that could either stand alone, indicating accessibility at a particular point in time, or vary across an intervention period and so be incorporated into an hedonic model as an accessibility characteristic.

This index comprised a spatial barrier represented by a decay measure (Allard & Danziger, 2002; Cervero et al., 1997; Sanchez et al., 2004), and an attraction or measure reflecting the 'opportunities' or jobs available. By merging the attraction and decay elements together, the index for each mode of travel was configured to be inversely correlated with a measure of proximity between locations namely travel time or travel cost. A distance based measure of proximity was discounted as inappropriate because distances between locations will generally undergo little change over a given period of time, and so would not allow a comparative evaluation.

Time and generalised cost by travel mode were more valid measures as these are likely to alter with the introduction of new rail or road infrastructure when making a comparison of job accessibility before and after a rail intervention. Transport costs will inevitably increase over a given period, and travel time will also change because of the intervention, particularly in the case of rail travel where this is linked to more distant destinations.

The key methodological issues considered here for measuring job accessibility are:

- Job reachability which takes into account transport mode, travel time and cost of travel.
- Commuting practicability which extends the concept of reachability by taking into consideration the transport mode and timing and location of services to determine if services exist between any two locations.Frontier effects which arise when constraining the pool of reachable jobs within administrative boundaries (workers will apply for jobs outside their residential region).
- Job suitability which considers the possibility of a qualitative match between the skill requirements of the jobs on offer and the individual skills of the job seekers. The preferred strategy would be to use a direct measure of vacancies instead of all

existing jobs but because of data availability constraints, the latter was not feasible so use here is made of jobs occupied by active workers instead of actual job seekers, as in (Korsu & Wenglenski, 2010).

Development of the index adopts a simplified gravity function approach, based on a matrix of distances between locations, and using standardised cost and time parameters. This involved:

- A generic accessibility index applicable to different travel modes.
- Measurability at different time intervals to detect impacts
- An attraction element representing the number of jobs available at other locations with scope to adjust for skills matching
- A negative exponential impedance function based on proximity between locations measured in terms of travel time or travel cost
- A commuting practicability dimension assessed on the availability and feasibility of travel to jobs

There were important characteristics specifically relating to more remote areas. Firstly, public transport may be infrequent, and therefore proximity measures will not necessarily reflect accessibility for commuting to jobs, and travel may be feasible only for a limited range of activities. Secondly, public transport may serve only a limited number of destinations, and not all travel modes will be available. Finally, the normal threshold limits for travelling to jobs may require redrawing where rail has made commuting easier.

The requirement was for an accessibility measure that could either be stand-alone - representing accessibility at a specific moment in time, or variable - capable of incorporation into a property price or employment model.

As the purpose of this accessibility measure was to estimate the impact of improvements in rail infrastructure on jobs, it was important to capture the proximity between origin and destination locations by considering time and cost as deterrents. These were weighed against the potential job pool in each destination location, matched to the occupational skills available in the origin location. Within the regional context of this study, the practicability of commuting may still remain unaltered even after the intervention.

A generic job accessibility index

Based on consideration of a combination of an attraction and decay function, and a gravity-based model (Hansen, 1959) a generic format for the job availability index $A_m(i,T)$ for origin location i, travel mode m, in year T was taken as:

$$A_m(i,T) = \sum_{j=1}^{n} O_{ij}(T)\, f(p_{ijm}) \,/ \sum_{j=1}^{n} O_{ij}(T) \qquad (1)$$

Equation 1 Generic job accessibility index

where:

- n represents the total number of locations within the specified regional boundary (e.g. case study region).
- m is travel mode (1 = Bus 2 = Car 3 = Rail etc.)
- $O_{ij}(T)$ is the attraction function for origin location i at destination location j (based on the number of jobs or other factors) in year T.
- $f(p_{ijm})$ is the impedance function which depends on the proximity p_{ijm} of i to j by mode m as represented by travel time or travel cost based on distance.

Hence there is an index for each location which accumulates opportunities weighted by distance to the opportunities in all other locations in the region. The index is 'normalised' through division by $\sum_j O_{ij}(T)$ (the total number of opportunities across the region in year T). This would indicate each location's relative share of the jobs available for the particular year in question. The calculation of the index for different years (T) allows monitoring at different intervals across the intervention period for a difference-in-difference or panel based comparison. The impedance function used in this accessibility index is

$$f\left(p_{ijm}\right) = e^{-\beta_m p_{ijm}} \qquad (2)$$

Equation 2 Impedance function format - exponential

where β_m represents the mode specific decay coefficient. Applying the impedance function, the index becomes:

$$A_m(i,T) = \sum_{j=1}^{n} O_{ij}(T)\, e^{-\beta_m p_{ijm}} \Big/ \sum_{j=1}^{n} O_{ij}(T) \qquad (3)$$

Equation 3 Generic index with impedance function

The β_m parameter would be estimated later empirically through observation of travel patterns (Setting the parameters for the impedance function**Error! Reference source not found.**) and this parameter could vary by context for different case studies as well as different travel purposes e.g. people may be prepared to travel further to work than to a cinema. The index was then expanded to cover key methodological issues: job proximity measures - travel time and travel cost, skills matching using local job comparison, and practicability of travel mode.

Proximity measure

Proximity between an origin and destination location is generally expressed in terms of geographical distance, travel time or travel cost, and influences the ability to seek and hold jobs. As one of the objectives for this index was to allow comparative evaluation over a rail intervention period, distance was not deemed an appropriate measure as it would generally undergo little change over that period.

Instead, proximity was measured for each transport mode using alternatively travel time and travel cost, applying the value of time (VOT) and standards for transport speed and other costs accessed through WebTAG and other sources (Wardman et al., 2013). The significant difference in accessibility between travel modes was affected by the speed of each mode of transport, waiting and walking time, and the unit cost of travel.

Although not used as a comparator, a reasonable estimate of distance between locations was required so that travel cost and travel time could be calculated. So before application to travel time and generalised travel cost, three possible distance measures were considered:

1. Euclidean distance: if location i has coordinates (x_i, y_i) and location j has coordinates (x_j, y_j) this equates to $\sqrt{(\mathrm{x_i} - \mathrm{x_j})^2 + (\mathrm{y_i} - \mathrm{y_j})^2}$
2. Manhattan (or rectangular) distance: the distance that would be travelled to get from one data point to the other if a grid-like path were followed and is the sum of the differences of their corresponding components. if location i has coordinates (x_i, y_i) and location j has coordinates (x_j, y_j) this equates to $|\mathrm{x_i} - \mathrm{x_j}| + |\mathrm{y_i} - \mathrm{y_j}|$
3. Network distance - the actual distance using the road network between the two locations

Using more sophisticated and precise measures such as travel times would involve computational difficulties, so there needed to be verification as to whether simpler Euclidean or Manhattan distances would be very different from network distances on the regional scale.

Job reachability

Job reachability was incorporated into the job accessibility index by considering the cost of travel, journey time and location of services for each transport mode and applying this to the impedance function. This required firstly an assessment of travel time and generalised cost of travel by delineating the area within which jobs could be reached by any given employee, so that jobs more distant from the employee's residential location were less reachable than those closer. In a comparative analysis between various forms of transport mode, differences in accessibility would be determined by the speed of each mode of transport, the waiting time and the unit cost of travel. This would be then extended to assess to consider commuting practicability i.e. whether there were available and feasible transport links between any two given locations.

Standardised travel time

In assessing travelling time between locations, key elements were the relative speeds of different transport modes, and a rational measurement of the actual travel distance. Travel times were measured by applying the average speed of the transport mode to the Euclidean distance between each zone’s geographic centroid. In reality, many journeys are multi-modal involving various forms of transport, but for the purpose of this simplified accessibility index, the core stage of the journey has been assumed single mode to allow comparison of accessibility for various transport modes. Total travel time between locations was calculated using a combination of distance and transport speed, with accessibility broken down by travel mode. A typical journey comprised four basic stages:

1) Origin to nearest stop/station (t_{WO})
2) Waiting for transport at stop/station (t_{WAIT})
3) Travel time in transport (t_{RIDE})
4) Nearest stop/station to destination (t_{WD})

Origin to nearest stop/station (t_{WO}) represents the time taken to reach a bus stop or station

- For car this is assumed to be zero.
- For bus a default distance of 500m has been adopted at walking pace to the nearest bus stop so t_{WO} = 0.5km.
- For rail, except for those locations within walking distance of a railway station, there will always be an element of travel at the beginning of the journey, albeit reduced after the intervention. This may vary largely and the distance to the nearest station has been assumed covered at the bus travel time and at bus speed.

Average waiting time (t_{WAIT}) For car mode it is assumed that waiting time is zero. For public transport this will depend on the service level (frequency) for the particular transport mode. In rural and disconnected regions, public transport service frequency may be as low as 1 per day up to a maximum of 1 per hour, and for commuting purposes, anything below 1 service per hour is probably not feasible. Scheduled waiting time for mode m in year T, $W_m(T)$ is estimated as half the headway i.e. the interval between services. For car mode it is assumed that waiting time is zero.

Travel time in transport (t_{RIDE}) represents the time spent travelling in the core stage of the journey using the main transport mode and has been based on the relevant distance for each transport mode. So for car this would be the distance between start and end points. For bus this would be the distance between start and end points minus 1km (which is the total distance to and from bus stops). For rail this would be the distance between the nearest origin and destination railway stations.

Nearest stop/station to destination represents the time taken from the nearest bus stop or station to the destination.

- For car this is assumed to be zero.

- For bus a default distance of 500m has been adopted at walking pace from the nearest bus stop so t_{WO} = 0.5km.
- For rail, except for those locations within walking distance of a railway station, there will always be an element of travel at the end of the journey, albeit reduced after the intervention. This may vary largely and the distance from the nearest station at the destination has been assumed covered at assessed at the bus travel time with bus speed.

Average speed of a transport mode $S_m(T)$ for transport mode m (m = walk (0), bus (1), car (2), rail (3), etc.) in year T was based on scheduled speed and compared with empirical experiences. This would vary depending on traffic congestion between any two locations, but standardised averages were calculated for the case study region.

Total travel time between locations i and j for mode m in year T is taken as:

$TT_m(i, j, T) = t_{WOm} + t_{WAITm} + t_{RIDEm} + t_{WDm}$ and was calculated using $S_m(T)$

Table 1 summarises the travel time calculations for all three modes.

Table 1 Travel time calculation by mode for each stage of the journey

Mode	Bus (m=1)	Car (m=2)	Rail (m=3)
t_{WOm}: Origin to nearest stop/station	$\frac{0.5}{S_0(T)}$	0	$\frac{dns_i}{S_1(T)}$
t_{WAITm}: Waiting for transport at stop/station	$W_1(T)$	0	$W_3(T)$
$t_{RIDE}m$: Travel time in transport	$(d_{ij} - 1)/S_1(T)$	$d_{ij}/S_2(T)$	$ds_{ij}/S_3(T)$
t_{WDm}: Nearest stop/station to destination	$\frac{0.5}{S_0(T)}$	0	$\frac{dns_j}{S_1(T)}$
total travelling time $TT_m(i, j, T)$	$W_1(T) + (d_{ij} - 1)/S_1(T) + \frac{1}{S_0(T)}$	$d_{ij}/S_2(T)$	$W_3(T) + \frac{dns_i + dns_j}{S_1(T)} + ds_{ij}/S_3(T)$

- d_{ij} = standardised distance between i and j

- $S_m(T)$ is the average speed for travel mode m in year T.

- dns_i = distance to nearest station from i dns_j = distance to nearest station from j

- ds_{ij} = distance between nearest stations to i and j

These are then applied to the impedance function and weighed against 'attraction' of job opportunities, to update job accessibility for mode m at location i in year t to:

$$A_m(i,T) = \sum_{j=1}^{n} O_{ij}(T) f(TT_m(i,j,T)) \,/ \sum_{j=1}^{n} O_{ij}(T) \qquad (4)$$

Equation 4 Index based on standardised time

For the impedance function $e^{-\beta_m TT_m(i,j,T)}$ this equates to the following for each mode:

- Bus $\quad e^{-\beta_1(W_1(T)+ (d_{ij}-1)/S_1(T)+\frac{1}{S_0(T)})}$
- Car $\quad e^{-\beta_2(d_{ij}/S_2(T))}$
- Rail $\quad e^{-\beta_3(W_3(T)+\frac{dns_i+dns_j}{S_1(T)}+ds_{ij}/S_3(T))}$

Generalised travel cost

In addition to travelling time, another key factor is the relative cost of different modes of travel. Total costs can be defined as the generalised journey costs in Equation 5

$$GC = P + U(m) \qquad (5) \qquad \text{(Balcombe et al., 2004)}$$

Equation 5 Generalised cost formula

where P is the sum of monetary costs and $U(m)$ represents the non-monetary (time) costs of a journey for transport mode m at time T. $U(m)$ can be calculated as the product of the total standardised travelling time of the journey ($TT_m(i,j,T)$) (from the previous calculation of standardised travel time), and the opportunity cost of the traveller's time value of time (VOT), so that:

$$GC = P + U(m) = P + VOT * TT_m(i, j, T)$$

Equation 6 Generalised cost with value of time

Monetary transport cost per mile is not always constant and speed of travel may be faster for longer as against shorter journeys. When comparing car with public transport, the monetary transport costs for a car could incorporate fuel costs, insurance, depreciation etc. whereas the monetary cost for public transport would relate only to the ticket fare for the distance travelled, but may be complicated by considering concessionary travel.

The monetary cost of travel could also allow for other factors such as car ownership, percentage of household budget for transport costs, and level of deprivation at the location, but in the interests of simplification they were not included in the index. For transport mode m in year T, assuming a unit monetary transport cost $C_m(T)$ and using the distance calculations used in Table 1, the monetary cost and non-monetary part of the journey were combined to give a generalised travel cost $TC_m(i, j, T)$ as shown in Table 2 below:

Table 2 Generalised cost calculation by transport mode

Bus	$C_1(T) * (d_{ij} - 1) + VOT * TT_1(i, j, T)$
Car	$C_2(T) * d_{ij} + VOT * TT_2(i, j, T)$
Rail	$C_3(T) * ds_{ij} + C_1(T) * (dns_i + dns_j) + VOT * TT_3(i, j, T)$

The job accessibility using mode m for location i in year T can be updated to:

$$A_m(i, T) = \sum_{j=1}^{n} O_{ij}(T)\, f(TC_m(i, j, T)) \,/ \sum_{j=1}^{n} O_{ij}(T) \qquad (7)$$

Equation 7 Index based on generalised cost

Commuting practicability

In comparing accessibility, Korsu and Wenglenski (2010) found it not sufficient just to calculate accessibility for each mode. Consideration had to be given as to whether:

- each travel mode was available between origin and destination
- there were feasible multi-mode combinations between origin and destination
- Average speed would vary depending on the congestion in each area and length of travel journey

In the context of remote or disconnected regions, public transport may run so infrequently and the timing of services for different purposes becomes crucial, so the time gap between inbound and outbound services is of paramount importance. Accessibility in rural areas can be approximated by measuring access to the network, so long as strict criteria are used for defining a 'useful' service.

The availability of travel by public transport between any origin-destination pair and the infrequency of public transport services should impact critically on the accessibility measure. For comparative purposes, the index would provide a measure of 'commuting practicability' by combining the availability of travel mode with feasibly practical multi-mode journeys. By considering all possible routes between any two locations, only combinations both available and feasible would count towards commuting practicability.

Post-intervention, other transport mode combinations may become both available and feasible for commuting. Consequently, a commuting practicability variable $\varphi_m(\mathrm{i,j,T})$ was added into the attraction element for each origin destination pair (i,j) at time T. This would equal 1 if both travel mode availability and feasibility between origin and destination equal 1, otherwise equal zero. So that even were available jobs at a destination, if $\varphi_{\mathrm{m}}(\mathrm{i,j,T})= 0$

they would not contribute to the attraction value. The generic job accessibility index then became as in Equation 8:

$$A_m(i,T) = \sum_{j=1}^{n} \varphi_m(i,j,T)\, O_{ij}(T)\, f\big(p_{ij}\big) \,/ \sum_{j=1}^{n} O_{ij}(T) \quad (8)$$

Equation 8 Allowance for practicability in generic index

In more remote locations, if services were hourly, then 30 minutes maximum transport travel time would be feasible, and if less frequent, then no commute would be viable.

Thresholds and frontiers

Frontier effects arose when reachable jobs were constrained to those living within a specified regional boundary, even though workers may apply for jobs outside that region. Travel thresholds or “frontiers" were an arbitrary measure representing the limits that people are willing to travel for work but this could be greater in rural and remote areas. According to the National Travel Survey 2016, between 2011 and 2014, miles travelled per head was 80% more in the smallest settlements and rural areas than in the Greater London Built-up Area.

The threshold distance for which potential accessibility value reaches zero was defined as the maximum travel distance observed for all commuters for each region, which was an aggregate over all transport modes. This depended on the case study region and the transport mode, but as a yardstick an average of 75 minutes was adopted based on aggregating UK Census Travel to Work information over all regions. (However, because the negative exponential function was short tailed, long distances would have limited effects on the accessibility estimation, and truncation thus did not lead to an important loss of information.)

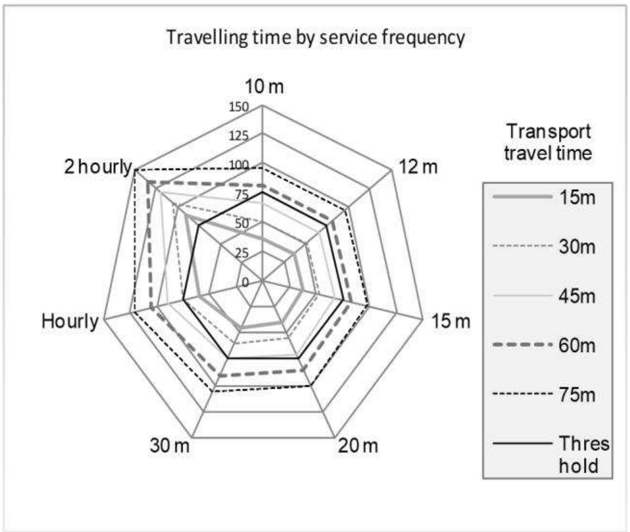

Figure 1 Travelling time by service frequency

Figure 1 highlights the relationship between service frequency, travel time and threshold for a range of "what if" values. This is illustrated in the shaded areas in Table 3 below highlighting trips where total travelling time exceeds the 75 minute threshold for various travel time combinations. This approach extended the potential model in order to take account of the case of commuters: people have access to opportunities not only in the area where they reside, but also in the area where they work.

Table 3 Table of travel times

Service Frequency	Waiting time	Time to transport	Time from transport	Transport travel time				
				15m	30m	45m	60m	75m
				Total Travelling Time				
10 m	5	10	5	35	50	65	80	95
12 m	6	10	5	36	51	66	81	96
15 m	8	10	5	38	53	68	83	98
20 m	10	10	5	40	55	70	85	100
30 m	15	10	5	45	60	75	90	105
Hourly	30	10	5	60	75	90	105	120
2 hourly	60	10	5	90	105	120	135	150

Job suitability

Even if a job were reachable, it may not necessarily be appropriate for every worker as individual characteristics determine the matching of jobs and workers, and job accessibility depends on the number of competitors that could claim to form a match. Job suitability refers to the possibility of a qualitative match between the skill requirements of the job offers and the individual skills of the job seekers (Ihlanfeldt & Sjoquist, 1998). To further allow for the relationship between job accessibility and employment in the case study region, and address the skills mismatch question, an element of occupational matching has been included. Building upon the work of Wachs and Kumagai (1973), the index incorporates and updates theory from Cervero et al. (1998) where conditions like occupational mismatches were explicitly accounted for in the job accessibility index.

The workforce in a particular location has access not only to jobs within its own residential region, but also to those outside its boundaries. Owing to data constraints, occupied jobs and active workers are often used instead of vacancies and actual job seekers (Korsu & Wenglenski, 2010), and for data availability reasons and the volatile movement in vacancies that is the approach used here (Ihlanfeldt & Sjoquist, 1998). Current jobs by occupation of residents at the origin location provided its skills profile and jobs by occupation reflected 'opportunities' at each destination location. The occupations are classified using SOC (Standard Occupational Classification) at the major group level of aggregation (23 categories) e.g. Management, Business and Financial etc..

Previously the attraction function $O_{ij}(T)$ had represented the opportunities (or jobs) available at destination location j in year T, so if occupation class is disregarded then all jobs are assumed available to all residents in i. The attraction function $O_{ij}(T)$ then was calculated as in Equation 9, and is the same for all origin locations.

$$O_{ij}(T) = \sum_{k} E_{jkT} \qquad (9)$$

Equation 9 Attraction function with no occupational matching

Occupational (or skills)) matching applied a weighting effect so that the closer the available jobs in j were to the skills profile in the origin location, the greater the attraction. The attraction function thus depended on the origin location i and would differ for each. Amending for occupational matching, the attraction function $O_{ij}(T)$ becomes as in Equation 10 based on Cervero et al. (1998)

$$O_{ij}(T) = \sum_{k} r_{ikT} E_{jkT} \qquad (10)$$

Equation 10 Occupational matching attraction function

where

- r_{ikT} = proportion of employed residents in location i working in occupational class k in year T
- k = 1 (executive, professional, managerial), 2 (sales, administration, clerical), 3 (services), 4 (technical) etc.
- E_{jkT} = number of workers in location j working in occupational class k in year T

The job-accessibility measure for location i in year T can then be refined using $O_{ij}(T)$ in Equation 10 to:

$$A_m(i,T) = \sum_j \varphi_m(i,j,T)\, O_{ij}(T) f(P_{ij}) / \sum_j \sum_k E_{jkT} \qquad (11)$$

Equation 11 Job Accessibility Index with skills matching

Providing an 'occupational match' accessibility index, the attraction function format added an important qualitative dimension into the analysis. Here the opportunities at location j were not considered equally available. For any origin location i, proximity to jobs in destination location j would contribute positively to the accessibility index based on the percentage of employed residents in location i matching the occupational opportunities in location j. Thus, if a large share of employed residents from say, Alloa worked in technical positions and a large number of available jobs in nearby Clackmannan were in technical fields, then this combination would contribute more highly to the attraction factor. Subtracting the standardised 'base' accessibility index (i.e. no occupational matching) from the standardised 'occupational match' index provided a 'match effect'—an indication of the relative importance of occupational matching as an input into the calculation of job accessibility. This index can also be applied without skills matching i.e. all jobs count as opportunities using $O_{ij}(T)$ from Equation 9 to replace that in Equation 11.

As the original attraction function (Equation 10) from Cervero et al. (1998) may not adequately reflect the number of potential opportunities in a destination location by occupation for the origin location the calculation was modified so that the closer the occupational match to the destination location, the higher the contribution to the attraction factor. The contribution of each occupation k to the attraction function in Equation 10 was thus changed from $r_{ikT} * E_{jkT}$ to $r_{ikT} * \sum_k E_{jkT}$ as a better representation of the relative number of jobs for that occupation in the destination location. However, as this should never exceed the total number of jobs for that occupation at location j in year T (E_{jkT}), so where $r_{ikT} * \sum_k E_{jkT} > E_{jkT}$ the contribution was adjusted to E_{jkT} to produce the amended attraction function (Equation 12).

$$O_{ij}(T) = \sum_k \delta_{ij}(k) \qquad (12)$$

Equation 12 Amended occupational matching attraction function

$$\delta_{ij}(k) = \begin{cases} E_{jkT} & \text{if } r_{ikT} \sum_k E_{jkT} > E_{jkT} \\ r_{ikT} \sum_k E_{jkT} & \text{otherwise} \end{cases}$$

Calibrating the index

In finalising the index a calibration process was required to estimate the β parameter to reflect behaviour in the case study region and different measures of proximity. The process consisted in defining two elements of the model specification: the mode related travel impedance and the set of potential destinations applicable to the case study region. In order to specify travel impedance, two steps were necessary:

1. Setting the parameters of the impedance function (e.g. the β constant).
2. Setting average values such as average transport speed and monetary cost

Case Study Example

Introduction

To illustrate the approach, the recent rail intervention of Stirling-Alloa in the Central Scotland Belt acts as a case study example (Figure 2). The Stirling-Alloa line serves Clackmannanshire, a previously isolated region classified as "urban with significant rural" now re-linked to the national rail network and the Glasgow-Stirling-Edinburgh axis.

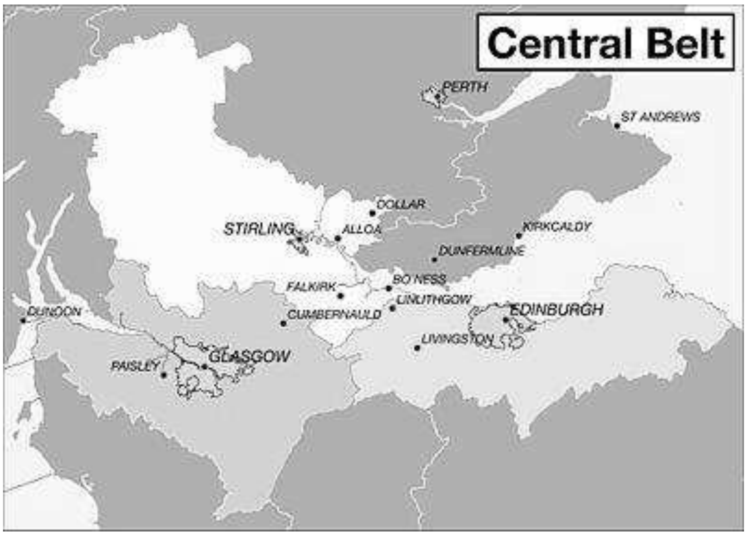

Figure 2 Geographical location of case study region
Source: Clackmannanshire Council

This case study region was defined by selecting 79 data zones which were mainly based in Clackmannanshire but including the outskirts of Stirling.

The rail intervention reopened a relatively small section of line, has been in place for 10 years, and represents a short extension which makes the rail network more accessible to a limited number of locations in the vicinity of Alloa (**Error! Reference source not found.**). The new line operates an hourly direct passenger service between Alloa, Stirling and Glasgow Queen Street stations with a 10 minute reduction in journey time to and from Glasgow, allowing passengers to change at Stirling for onward travel to Edinburgh.

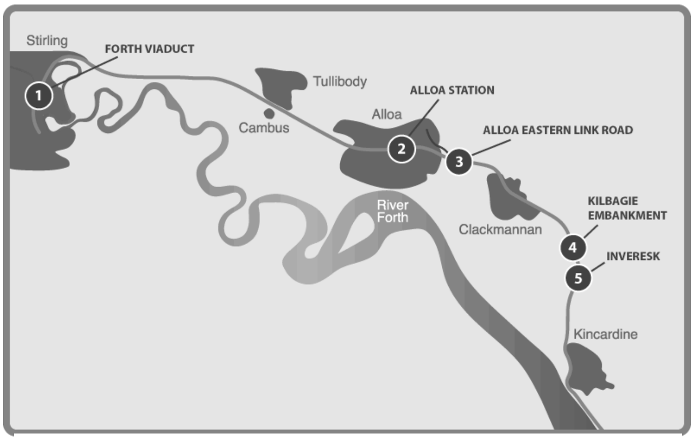

Figure 3 Stirling-Alloa rail link
Source: Transport Scotland

The region comprises a mix of smaller communities previously remote from the rail network and in a geographically cut-off location. The region has declined economically over the years, and there are pockets of deprivation in the region with ten data zones classified as the 15% most deprived areas in Scotland. Employment is dominated by the production sector (39%) and education and health sectors (22%) with regional employment levels (2015) at 71.6% compared to Scotland at 73.1%. The workforce is slightly lower skilled than nationally with 17% of employees working in professional occupations compared to the Scotland and UK averages of 20%.Proximity measure

The distance measures were applied for a selection of regional locations in the case study region. This was validated for randomly selected journeys by comparing calculated travel distances in the first two measures with travel distances times obtained from on-line mapping providers (Google Maps) for the third measure. Pearson correlation coefficients were then calculated in order to assess the strength of the associations between the three measures for observed commuting trips. Results (**Error! Reference source not found.Error! Reference source not found.**) demonstrated that the associations between all three measures were very strong (correlations above 0.97), and from **Error! Reference source not found.** it could be concluded that Euclidean distances were a good approximation of the other two more specific distances on a regional scale. Therefore to keep the calculations as simplified as possible it was decided to base it on Euclidean-based distance.

Table 4 Correlation of distance measures

	Euclidean	Manhattan	Network
Euclidean	1.000		
Manhattan	0.980	1.000	
Network	0.979	0.960	1.000

Setting the parameters for the impedance function

It was necessary to determine the exponential function decay parameter *(β)* for the case study region, travel mode and year. The method used was to produce the best fit for travel behaviour and for the time and cost proximity measures by performing both linear and non-linear regression analysis between distance to work and percentage travelling that distance by data zone using transformed and non-transformed data respectively.

Data were log-transformed and linear regression analyses performed for several distance exponents in order to find the best fit with distance to work as the independent variable and percentage travelling that distance as the dependent variable .i.e. the minimal standard error of estimate. The regression model took the form $log(P_i) = \propto + d_{ij}\beta$ where P_i is the probability for interaction at distance d_{ij} but because probability reaches 1 at null distance, the constant term $\propto$ was taken as zero. For non-linear regression analyses, the model was of the form $P_i = e^{-\alpha d_{ij}\beta}$ and initial parameters used in the iterative process had been set to values relatively close to those expected. Table 5 summarises cumulative distances travelled to work for the Stirling-Alloa region aggregated over 79 data zones comprising the case study regional boundary. This indicates that on average 49.36% of the working population travel at least 10 km to work, and this tails off gradually up to 40km (78.95%).

Table 4 Decay effect of travel distance

Source: UK Census 2001

Distance	Average
> 2 km	87.58%
> 5 km	72.60%
> 10 km	50.64%
> 20 km	32.03%
> 30 km	26.18%
> 40 km	21.05%
> 60 km	13,89%
> 100 km	11.70%

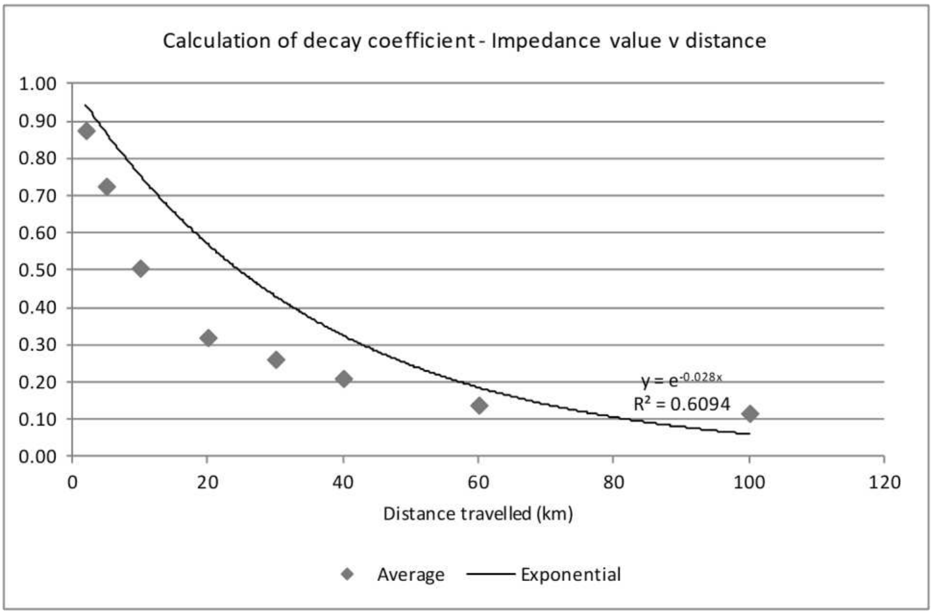

Figure 4 Example calculation of decay coefficient

Source: UK Census 2001 - Travel to work by data zone for Stirling-Alloa case study data

By plotting observed data and the predicted values of the regression model, some differences were found: the non-linear regression model tightly fit observed data for intermediate distances, but seemed to underestimate probabilities for shorter and longer trips. In contrast, the linear regression model seemed a better fit to probabilities for longer trips but clearly underestimated values for short and intermediate distances (**Error! Reference source not found.Error! Reference source not found.**).

Setting average values

For the case study region, average speed was based on scheduled speed and compared with available empirical experiences. To come up with a price comparison for the individual modes of public transport, a price per km was calculated based on train, bus and car mode:

- Train: Train connections for up to ten popular routes were analysed in terms of distance and current price through consulting various on-line sites (Google, Rome2Rio, ViaMichelin). The average price available was used in order to calculate standard cost per km. The cost for earlier years was then extrapolated using the train fares price index.

- Bus: Ten popular connections were analysed in terms of distance and current price using similar sources as for rail travel. The average price available was used in order to calculate standard cost per km. The cost for earlier years was then extrapolated using the bus fares price index.

- Car: Rather than use estimates of actual costs of motoring, a perceived standardised cost was calculated omitting depreciation as an "invisible" cost but comprising fuel cost with an allowance for overhead and maintenance costs. Historical UK fuel prices for years 1991 to 2017 were sourced from UK Government Quarterly Energy Prices (2018) and factored up to allow for changes in everyday running costs based on an annual average of 16000 km as suggested in DfT:Vehicle mileage and occupancy (2013) and at 35 miles (56km) per gallon from DfT Statistics (2014).

- Walk: Total walk time adopted the standard walking speed of 4.8 Km per hour or 80 metres per minute as suggested by Wu and Hine (2003).

Average speed of a transport mode $S_m(T)$ was based on averages calculated for the case study region from the popular bus and rail routes sampled above, and calculated by dividing the average route distance divided by average speed for that route for each travel mode. **Error! Reference source not found.**Table 5 shows the average values used for Stirling-Alloa applied in estimating the standardised monetary cost of a journey for each transport mode.

Transport Mode	Year	Transport Speed (km/hour)	Service Frequency	Headway (mins)	Monetary Cost of Travel per km
Bus	2001	40	1	30	£0.10
	2011	40	1	30	£0.16
Car	2001	50	0	0	£0.29
	2011	50	0	0	£0.48
Rail	2001	65	1	30	£0.16
	2011	65	1	30	£0.25

Table 5 Standardised monetary cost and speed values used in index calculation

Using the formulas derived previously in Table 1 and Table 2, the values in Table 5 are applied to calculate standardised time and generalised cost for each travel mode to produce a measure for the accessibility index.

Commuting practicability

In the simplified Alloa to Glasgow example in Table 6**Error! Reference source not found.** availability equals 0 if the mode combination does not exist in year T, and 1 where a possible mode combination for commuting exists.

Rail access was available between Alloa and Glasgow, but total travelling time by other modes to the nearest station (Stirling) was an impractical commute, and the only feasible travel method was by car. The result of combining availability and feasibility for different commutes and the resultant value of φ are shown in Table 6**Error! Reference source not found.**.

Table 6 Multi-mode stages Alloa to Glasgow via Stirling

Multi-Mode Stages		Route	Pre-intervention			Post-intervention		
1	2		Available	Feasible	φ	Available	Feasible	φ
Bus		Alloa-Glasgow	1	0	0	1	0	0
Bus	Rail	Alloa-Stirling-Glasgow	1	0	0	1	1	1
Car		Alloa-Glasgow	1	1	1	1	1	1
Car	Rail	Alloa-Stirling-Glasgow	1	1	1	1	1	1
Rail		Alloa-Glasgow	0	0	0	1	1	1

Calculating the accessibility index

Having determined the specific cost and decay parameters for Stirling-Alloa, the next stage was to compare the job accessibility index alternatively based on travel time and travel cost before and after the intervention broken down further by applying either job skills matching or no matching after allowing for commuting thresholds.

The UK Census provided data on employment by occupation and industry, modes of travel to work, distance to work and car ownership data as well as age profile, occupation profile and economic activity both pre-intervention (2001) and post-intervention (2011). This covered distinct years spanning the introduction of the rail link providing a useful before and after comparison. Nomis supplied additional labour market data including vacancies by occupation and data zone from 2004 onwards, and further employment data were extracted from the Annual Population Survey and Employment Structure via BRES. Population data was accessed via the UK Census 2001 and 2011, National Records of Scotland and Scottish Neighbourhood Statistics. Key routes and traffic flow data were accessed by Transport Scotland and an analysis of bus routes and times through access to individual timetables and schedules. Data was aggregated to data zone level as the lowest common denominator. OS Post Code reference data was used to measure distances between job origins and destinations. Location data for all data zones generated a distance matrix highlighting differences in spatial accessibility to jobs

The job accessibility index was calculated separately based on standardised travel time and generalised travel cost applying the calibrated values. The index was measured pre- and post-intervention by taking into account rail infrastructure changes and using the job situation in pre-intervention years to reflect change in accessibility due only to the rail intervention, and discounting changes in the job market post-intervention. The region was also divided up for analysis into treatment and control groups, where treatment groups represented those locations experiencing a change in access to the rail network, and control groups represented similar socio-demographic locations not affected by infrastructure changes. There was further subdivision based on the application of skills matching or no matching.

Findings

Movements in job accessibility were compared across 79 Scottish data zones in the region for periods spanning the rail intervention to highlight how changes in job accessibility have impacted in specific locations.

Figure 1 and Figure 2 compare the effect of job skills matching based on an impedance of standardised travel time and generalised cost both before and after the intervention. They suggest that lack of job skills matching tends to overestimate the attraction factor of job opportunities. There is a wider difference when the index is based on travel cost rather than travel time, suggesting that cost is more of an impediment than time. The difference between pre- and post-intervention shows an impact due partially to the change in proximity brought by rail.

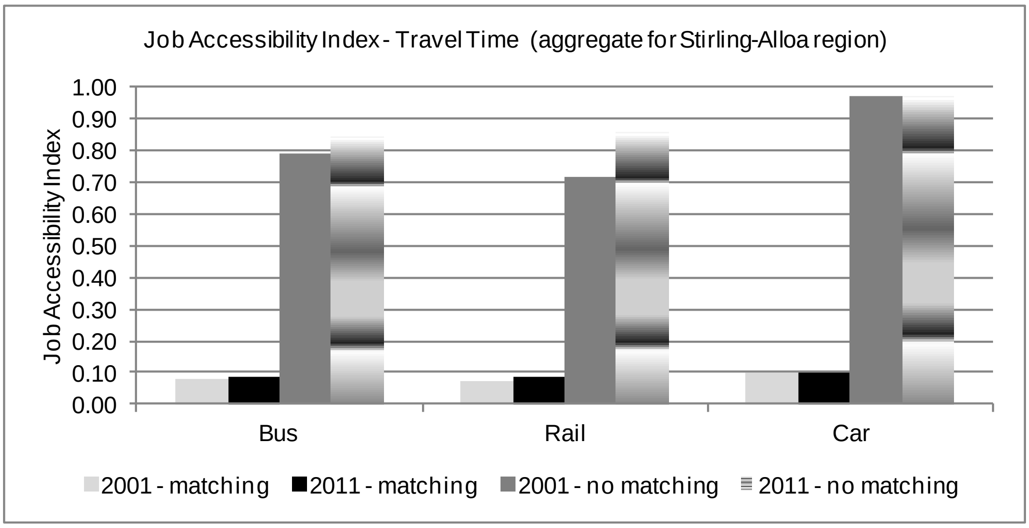

Figure 1 Job Accessibility index based on travel time (from UK Census data)

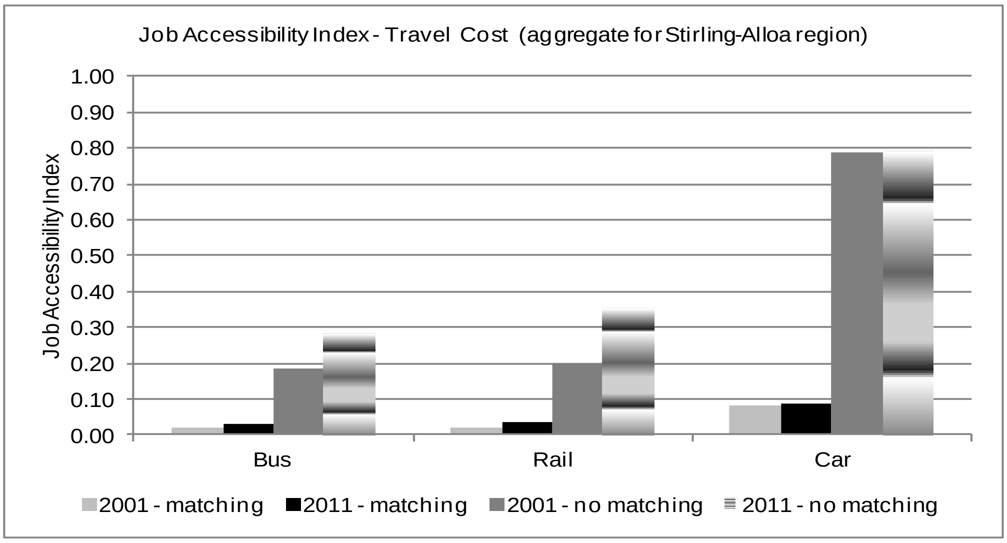

Figure 2 Job Accessibility index based on generalised travel cost (from UK Census data)

Using both a travel time and generalised travel cost basis both with and without skills matching, accessibility to rail mode increased post-intervention for both the treatment and control group, but was marginally greater for the former on a cost basis and lower on a time basis which suggested that there was more benefits from cost as a basis (Table 7). Applying skills matching accessibility to rail mode surprisingly produced a similar percentage increase as that estimated with no matching, which may suggest that because the region studied is small and compact there is either a similar skills set or skills requirement across the region. The larger percentage increase when comparing time and generalised cost as a basis reflects both the impact of the value of time in the calculation and the rail routes available after the intervention. Prior to the introduction of rail there was a disproportionately high fare-based cost of interconnecting multimodal journeys which are no longer required post-intervention.

Table 7 Change in job accessibility- rail mode (2001-2011): Stirling-Alloa

		with skills matching			without matching		
Group	Method	pre	post	% change	pre	post	% change
Treatment	Cost	0.022	0.039	80%	0.212	0.380	80%
	Time	0.075	0.088	17%	0.740	0.867	17%
Control	Cost	0.019	0.033	71%	0.192	0.327	70%
	Time	0.070	0.085	23%	0.692	0.850	23%

Pre- and post-intervention differences show an impact due partially to the change in proximity brought by rail. All results are aggregated job accessibility indexes for all 79 data zones within the Stirling-Alloa region, and suggest that in this case, job skills matching provides a similar relative change in accessibility.

Conclusion

The job accessibility index developed here has attempted to provide an easily calculable format which focuses on remote rural or disconnected regions without resorting to detailed network analysis. It can act either as a stand-alone comparative measure or inclusion as an accessibility characteristic in a hedonic model in conjunction with other characteristics e.g. property and socio-demographic profiles. It is particularly applicable in the particular context of more remote areas in allowing for local job skills, and public transport service frequency. In particular the concept of 'commuting practicability' is considered where although there is transport availability, this may not translate into feasible use for commuting because of poor public transport service frequency.

The inclusion of skills matching is also shown as being pertinent in the context of isolated and disconnected regions (although not as evident in the Stirling-Alloa example where many locations have a similar occupational split.). Here an alternative method is adopted to that used in Cervero et al. (1998), which more closely reflects the nearness of skills matching between locations.

Analysis of the effect of job skills matching based on an impedance of travel time and generalised cost, both before and after the intervention has indicated that:

- Not allowing for job skills matching may tend to overestimate the attraction factor of job opportunities at other locations as they may not always be relevant .
- There is a wider difference pre- and post-intervention when the job index is based on generalised travel cost rather than travel time which may suggest that more value is put on the cost of travel in relation to the value of time in this particular regional context, cost being a more sensitive indicator in expressing proximity.
- The difference in job accessibility for rail mode pre- and post-intervention when comparing treatment and control groups indicates an impact due partially to the change in proximity to the rail network for the treatment group.

In simplifying the calculation there are several weaknesses to be taken into account:

- Under or over-estimation of accessibility by ignoring subjective representations of distance
- It does not allow for variation in estimation of speed and cost of travel
- The occupational categories used may be too broad
- It does not adequately allow for transfer between similar occupation types.
- It measures job attraction by using the skill profile of the residential workforce rather than those searching for jobs.

Based on consideration of the above limitations, the index is being further developed to be more representative. This includes allowance for congestion and local differences in density and frequency in the transport network, deprivation levels to reflect commuting costs relative to income, and further exploration of frontier effects and extending the pool of reachable jobs outside of administrative boundaries.

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