ECONOMETRIC ANALYSIS OF THE LINK BETWEEN PUBLIC TRANSPORT ACCESSIBILITY AND EMPLOYMENT

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Abstract

Modern transport policy analysis has ceased to be mainly about transport impacts and is now focussed on the effects of provision and policy upon the operation of the economy and society. For people on the edge of the labour market, many of whom do not have access to other forms of transport, public transport is a very important source of accessibility to jobs.

This analysis addresses what we see as a key research gap in Britain - whether there is a systematic variation in the level of employment at the local level with the quality of the public transport network. To address this we apply regression analysis to explain employment as a function of accessibility and other local labour and socioeconomic variables. Our data were based on a cross-section of output areas from the English part of the 2011 Census. We found a statistically significant relationship suggesting that, all else being equal, areas with shorter public transport times were associated with higher employment levels.

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INTRODUCTION

Modern transport policy analysis has ceased to be mainly about transport impacts and is focussed on the effects of provision and policy upon the operation of the economy and society. For people on the edge of the labour market, many of whom do not have access to other forms of transport, the bus and other forms of public transport (PT) are very important sources of accessibility to jobs. Analysis of the English National Travel Survey (Mackie et al, 2012), found that 30% of people are frequent bus users (once a week or more) with over half of 16-19 year olds and over a third of 20-29 year olds frequent bus users. 70% of those with no car available use the bus frequently compared with 20% of those with car available.

In this paper we aim to empirically model the sensitivity of employment to differences in PT accessibility. This is a relatively unexplored area in Britain with difficult data requirements but here we make use of the 2011 Census, national spatial data sources and additional data provided to us by the UK's Department for Transport (DfT) based on data published in DfT (2014a).

Our research approach is to estimate cross-sectional models of employment and PT travel times separately for each of four levels of urban density across England. Our data is generated by matching information from the 2011 UK Census at the middle-layer super output areas (MSOA) with PT accessibility data from the DfT. These data permit us to investigate the relationship between spatial differences in PT (and car) accessibility and differences in employment rates, controlling for localised factors such as population, car availability etc.

Our work contributes to the existing research in a number of ways. First, the analysis looks at this relationship across the population at large, not just the vulnerable. We derive our results from persons living throughout England, not just in one state or region, as many other studies have done, allowing us to compare the labour supply impacts in different area types. Our findings add to the empirical evidence base for the linkage between public transport accessibility and employment to help inform UK public transport policy. Our results are potentially transferable to applications where the sensitivity of labour supply response to improvements in accessibility is required, such as in the estimation of wider economic impacts of public transport improvements. We use an Instrumental Variable approach to address the issue of causality in the relationship between public transport accessibility, car ownership and employment.

It is not the purpose of this paper to examine the appropriate context for valuing the contribution of employment to the economy. For an up to date summary of the state-of-the-art in examining the linkage between transport and the economy and its context within current appraisal practice, see Venables et al (2014).

1 LITERATURE REVIEW

1.1 Introduction

The link between transport accessibility and employment has long been a policy issue and a research area in the planning, geography and transport literature. Much of the early research was linked with the spatial mismatch hypothesis. Segregation of housing by race and the increased suburbanisation of employment in the US led to difficulties for low skilled minority workers accessing employment leading to a spatial mismatch between workers and employment (Kain, 1968).

In their review of the SMH literature, Ihlandfeldt and Sjoquist (1998) list limited public transportation as a premise behind difficulties in finding work for minorities. A strand of this SMH research (Studies such as Sanchez (1999), Ihlanfeldt and Young (1996), Taylor and Ong, 1995, Kawabata (2003), Berechman and Paaswell (2001), Yi(2006)) has emerged to establish whether transport accessibility is associated with employment outcomes. Some more recent studies focus on whether the spatial mismatch problem could be addressed through improving public transport access to suburban jobs (Holzer et al., 2003, Tyndall (2015), Ong and Houston (2002)). Other studies look at impacts of improved access to both forms of transport (Cervero et al (2002), Smart and Klein (2015) and Blumenberg and Pierce (2014)). The US based findings are clear in the importance of access to private transport but inconclusive as to the relative importance of private and public transport.

In a European context there is a different spatial distribution of residential areas. City areas are generally less dispersed with more developed public transport networks than in the US. Over the past few decades European city areas have become less compact with the city centres hosting more wealthy neighbourhoods and a higher concentration of skilled employment areas with less affluent areas and lower skilled jobs in the suburbs (Korsu and Wenglenski (2010) and Turok and Edge (1999) for the British context). In Britain this dispersion remains a lot less than in the US (Summers, 1999). Compared to the US, there are lower car ownership levels and consequently higher use and development of public transport networks (Downs, 1999). This emphasises the important role that public transport plays in facilitating employment. Houston (2005) highlights the scope for both improvements in public transport access to out of town employment sites and better access to private transport to promote employment.

In Britain there are considerably fewer studies but some limited evidence for the SMH (see McQuaid et al, 2006), based largely around segregation by skills/demographic characteristics rather than by race, ie lower skilled workers can be employed far from where they live. Houston (2005) also highlights that those in social housing are more likely to be affected by unemployment due to their lack of mobility. Patachini and Zenou (2005) examine job search intensity using British sub-regional aggregate data and find higher commute times and lack of car access yield less search intensity. McQuaid et al (2001) also look at job search behaviour in Edinburgh and find areas of high unemployment were typified by lower willingness to travel to work times. Fieldhouse (1999) examines the racial dimension but finds the SMH doesn't explain differences in unemployment rates amongst ethnic minorities in London. Whilst ethnic minorities were living in high unemployment areas, unemployment was a general problem for all workers in these areas and there was no evidence this was a product of the mismatch of people and jobs, but rather linked to housing, skills and demographic factors. Dujardin et al (2008) and Gobillon and Selod (2006) find similar limited evidence of SMH in that urban employment in Brussels and Paris respectively is affected by socioeconomic factors but not by accessibility to jobs.

Studies deal with accessibility in different ways. In some studies accessibility is simply a transport measure captured by the number of public transport nodes within a particular radius (Ong and Houston (2002)) or the proximity to the nearest transport node (Holzer et al, 2003; Sanchez, 1999) or measures of route density (Rice, 2001). Other approaches look at accessibility to jobs either by mode or on average, using average commute times (Ihlanfeldt and Sjoquist, 1991; Cervero et al 2002; Ozbay et al, 2006; Berechman and Paaswell, 2001) or numbers of jobs within a particular public transport travel time radius (Smart and Klein, 2015, Gibbons et al, 2012). More sophisticated gravity based formulations (eg Kawabata, 2003, Yi, 2006; Sanchez et al 2004) account for the spatial distribution of employment with an impedance measure based on travel times or costs.

A crucial aspect to such analysis is on establishing a causal relationship between accessibility and employment. Transport accessibility does not vary randomly between areas. As Tyndall (2015) observed, there is a possible codetermination between economically developed areas and areas with better public transport accessibility. However, the linkage could possibly work in reverse - Glaeser et al (2008) observe that the urban poor without cars move to areas with better public transport access to improve their access to employment opportunities. Recent work undertaken by the What Works Centre for Economic Growth (2015) has highlighted the importance of establishing (and the current lack of) a credible evidence base on the linkage between transport and the economy. Of the six studies which passed its criteria for consideration looking at employment effects of road based projects, only two actually identified positive employment effects. They found no high quality evaluations on employment effects of rail infrastructure, trams, buses and active modes on any economic outcomes.

1.2 Public Transport and Employment

Public transport represents an option for improving access to employment opportunities. However, as noted by Ihlanfeldt and Sjoquist (1998), other factors such as lack of information on job availability and discrimination and lack of skills are at least as important in affecting employment levels for inner city, low income groups. Whilst there is much work in the subsequent literature on the spatial separation between jobs and homes, there is less work on the impact of commuting times or distances.

1.2.1 Public Transport and Local Labour Market Outcomes

Sanchez (1999) uses a cross section of block[4] group census data and GIS to analyse the location and employment characteristics of workers with varying levels of accessibility to transit for the cities of Portland Oregon and Atlanta Georgia. He finds that transit access, but not always frequency, is a significant factor in determining average rates of labour participation of areas within these two cities.

Work by Buchanan (GLA Economics 2009), forecasted the distribution of future employment growth in Greater London, specifically focusing on the relationship between employment and

[4] Blocks are statistical divisions of census tracts, generally defined to contain between 600 and 3,000 people

public transport and highway accessibility. Accessibility indices were calculated using a gravity model applied to zonal population and zone-to-zone generalised time measures. They found that public transport accessibility explained around 85% of employment density and conclude that employment clustering in Central London is almost entirely dependent on public transport access. However, their analysis includes no other localised explanatory factors.

Very few aggregate studies deal with the endogeneity between transport accessibility and employment outcomes. The ideal way to establish causality is to compare employment impacts in areas which have been subject to a random natural shock or policy induced 'quasi-random' change in transport accessibility with control areas which haven't had such changes in accessibility. Gibbons et al (2012) estimate employment impacts using a panel database of employment at the ward level married to measures of road construction schemes. They deal with the issue of endogeneity by looking at the impact of these schemes in areas close to (10-30km), but not directly on top of these schemes, the implication being that these are incidental to the main target area of these schemes and can thus be considered as 'quasi random' in the selection of treatment areas. Their measure of accessibility is an index capturing the amount of employment reachable per unit of travel time, based on ward to ward travel times. They use a 'fixed effects' approach to avoid any bias arising from the correlation of unobserved time invariant area level effects with accessibility. They find a 10% improvement in accessibility leads to around a 3% increase in the number of businesses and employment up to 30km from the site, although the estimates range between zero and 10% depending on sector and specification.

Ozbay et al (2006) look at the issue of accessibility measures using county-level data from New York/New Jersey for the year 2000. They find accessibility (measured in units of weighted travel time between residential and employment locations) is positively affected by public transit and car travel times and emerges as a significant determinant of employment for all job types. They also examine the issue of causality by estimating accessibility as a function of employment, which suggests that employment growth does influence accessibility.

From the employers' perspective, it is logical to assume that employers locate near transport nodes thus some of the employment effect observed by better access might be through re-location of firms. Holzer et al (2003) exploit the natural experiment of the extension of the San Francisco Bay heavy rail system which provided an exogenous increase in accessibility to employment opportunities. By surveying employers they established a higher likelihood, post intervention, for employers close to the line to hire Hispanic (but not Black) workers from deprived neighbourhoods. This again highlights the role that public transport can play in alleviating the problems of the spatial mismatch.

1.2.2 Public Transport and Individual Labour Market Outcomes

There is a considerable amount of literature on estimating the employment status for individuals (e.g.. unemployed or not) as a function of personal and regional characteristics e.g. for an early application see Gunderson (1980). Logit and probit models are standard tools in examining probabilities of employment and labour force participation. These models are analogous to regression models but estimate the probabilities of a discrete outcome for an individual.

Many such models use cross sectional data in specific areas, focusing on the role of accessibility without examining endogeneity issues. For example, Yi (2006) models employment outcomes of individuals in the Houston metropolitan area and finds increased accessibility to jobs by public transit improves the level of employment, particularly part-time but also that private mobility would be more effective than policies improving public transit access. Ong and Houston (2002) model individual employment outcomes of single women with no car access in Los Angeles County, finding that the level of transit service near a recipient's home has a statistically significant contribution to increasing the probability of employment.

Some studies compare outcomes between different metropolitan areas. Kawabata (2003) conducts a segmented analysis focusing or car owning and non car owning sub sections of the population. Using a job accessibility measure combining job and public transport access, she finds evidence to suggest that job accessibility for captive public transport users plays a more significant role in highly auto-dependent metropolitan areas than areas with well developed public transport. Her work also suggests, contrary to some of the spatial mismatch literature, that central city neighbourhoods offer greater job accessibility than suburban areas.

Other studies have a broader spatial scope, looking at a number of areas. In a study of individual labour market outcomes across 62 US cities, Rice (2001) finds density of public transit routes has a significantly positive effect on the probability of employment for the low education population (but not the overall population). A 10% increase in public transport density is associated with an increase in 0.6% in the probability of employment – roughly half the size of effect of a comparable increase in car ownership. Sanchez et al (2004) models individual level participation outcomes in six metropolitan areas in the US, finding public transport frequency and employment access were not significant determinants, whereas other personal and household level characteristics were.

Panel data approaches are potentially more revealing, as they involve repeated observations on individuals over time, therefore controlling for unobserved individual and area level factors which influence temporal changes in employment. For example, Cervero et al (2002) use a panel data approach to look at changes in employment status amongst welfare recipients in an area of California. Whilst access to private transport emerges as a much stronger determinant of labour market outcomes, there is an impact from better transit access. Smart and Klein (2015) use a representative national US panel data sample of individuals to model changes in labour market outcomes. Results indicate that better access to automobiles help families unemployment. Access to high-quality transit, however, has the opposite association suggesting neighbourhood characteristics are not fully controlled for.

The above cross sectional and panel studies do not address the issue of endogeneity, so causality in the relationship between car ownership and public transport access and employment is not established.

Blumenberg and Pierce (2014) analyse the impacts of a housing experiment which involved the random assignment of vouchers to enable deprived families to move out of low income neighbourhoods in five metropolitan areas in the US in the 1990s. Based on the proportion of the voucher receiving families that moved to neighbourhoods with better transit, they find better access to public transport (a feature of the better areas) helps maintain employment but not find employment. Keeping or owning a private vehicle on the other hand is a significant factor in finding employment (although they acknowledge it could be the employment facilitating car ownership as direction of causation cannot be established).

Tyndall (2015) uses reduction in public transport access to certain neighbourhoods in New York following Hurricane Sandy in 2012 as a natural experiment allowing the causal linkage between public transport and unemployment to be identified. Using a difference in difference approach to identify the impact of R train closure on neighbourhoods, the study finds strong evidence that public transport access impacts on local unemployment, particularly for those with limited private vehicle access.

Dujardin et al(2008) remove the endogeneity between location and employment by focusing on young adults whose are living with their parents and thus their location is exogenous. Their results were not largely affected by this approach.

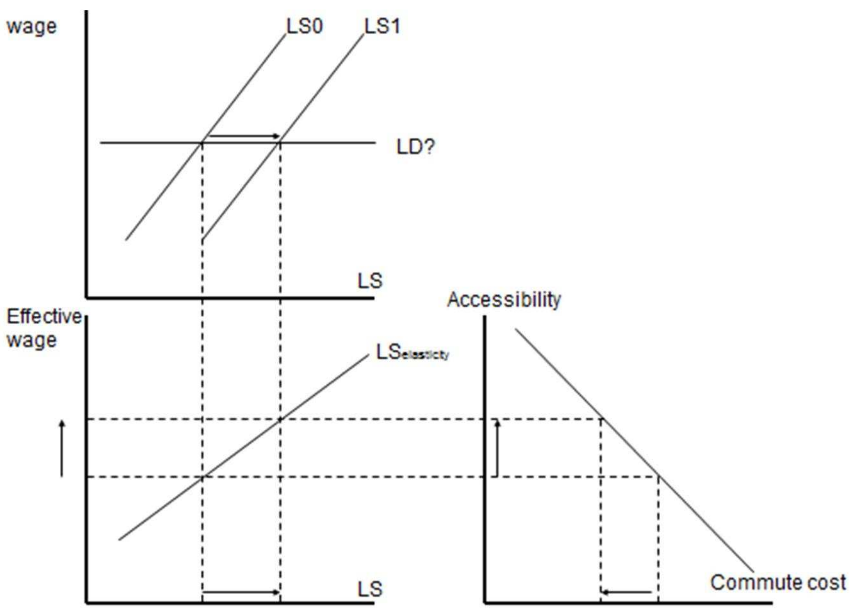
1.3 Conceptual framework

1.3.1 Transport Accessibility and Labour Supply

Clearly the effects of better PT will come about through changes in travel times, reliability, comfort or fares. These are the mechanisms by which improved accessibility is created. The appraisal treatment of such impacts is well documented in WebTAG (DfT, 2014b) and elsewhere. However, below we present a simple framework by which such a linkage exists, consistent with general Green Book (HM Treasury, 2011) principles, specifically the full employment assumption and assuming demand for labour is elastic at the going wage rate, gross of commuting costs, for the relevant class of labour.

A reduction in commuting costs flows through to labour, increasing the wage net of commuting costs and stimulating an increase in labour supply as shown in Figure 1-1.

Figure 1-1 Impact of Change in Commute Cost on Labour Supply



Under conditions of perfect competition the value of the increased employment is captured through commuting time savings. However, where such conditions do not hold, for instance when there are tax distortions in the labour market, there are additional wider economic impacts not captured by time savings. These labour market effects are valued in terms of the additional tax revenues generated by the change in labour supply (see DfT, 2014c).

There are further market failures to those described above, as discussed in Laird and Mackie (2009). Transport schemes that increase employment in areas of high unemployment will have positive economic impacts that are not encapsulated in transport user benefits. Boardman et al. (2011) describe unemployment rates of 5% or below as purely frictional and any such areas can reasonably be considered to be notionally at full employment. A simplifying and reasonable assumption (that is typically used in CBA) is that there is full employment in the regions from which the labour is displaced, so the loss of welfare associated with reduced employment in these areas is fully captured through the change in commuter user benefits in these regions. Rates above 10% represent structural unemployment, so reductions in unemployment around this rate represent net increases in employment. (Between 5-10% this effect is partial). In this way, there is a net economic impact from a redistribution of employment to the area with structural unemployment.

2 METHODOLOGY

2.1 Cross sectional Model

We estimate a cross sectional model of employment matched to transport accessibility and socio-demographic data. The cross sectional approach allows us to investigate the relationship between spatial differences in public transport (and car) accessibility and differences in employment, controlling for other localised factors.

The level of aggregation is at the Mid Layer Super Output Area (MSOA), constructed within local/unitary authority boundaries to contain populations between 5,000 and 15,000 individuals, and between 2,000 and 6,000 household units. This allows us to utilise the 2011 UK Census data at the same level of aggregation, giving 6786 observations on social and labour market measures for England, matched to PT accessibility data from the DfT.

In order to estimate this model we conduct fixed effects regression analysis by estimating a set of constants for each of 345 Local Authority Districts (LADs), each containing a number of MSOAs, which capture area-wide unobserved characteristics influencing employment (for example, natural resources, local geography, the presence of large historical employers in an area, industrial mix and a skilled labour pool).

Our model formulates employment in MSOA i within LAD k in the following way:

$$Employment_i = f(A_i, C_{LADk}, V_i)$$

where:

A_i represents the accessibility measures for area i;
V_i are variable factors such as population and labour force composition variables
C_{LADk} are constants capturing the impact of unobserved variables within LAD area k

We use a log-linear functional form to derive proportional responses (elasticities) for the impact of differences in travel time on employment directly from the parameters. Variables reported as levels are logged, however proportional variables (such as car unavailability, gender mix) are not logged.

2.2 Endogeneity and Instrumental Variable Analysis

An important issue within any analysis of this nature (as highlighted in the literature review) is to understand if any explanatory variables might be endogenous within the system. We considered two possible endogenous explanatory variables: public transport accessibility and car unavailability. Employment may possibly have a bearing on public transport provision if differences in employment have differential effects on PT demand which are responded to by operators. The relationship could be that higher levels of employment cause increased demand for PT services due to more people travelling to work, all else equal. Different levels of employment may also have differential effects on car unavailability in that higher levels of employment may facilitate higher levels of car ownership through an income effect. Glaeser el al (2008) also identify another source of endogeneity in that poorer people are less likely to be employed and therefore are less likely to be able to afford car ownership. This, in turn, means they are therefore more likely to be drawn to areas with better public transport accessibility.

We investigate this issue of endogeneity through the use of instrumental variable (IV) approaches to control for the endogeneity between employment and both PT accessibility and car unavailability.

There are two requirements for a good instrumental variable. Firstly, the instrument must be highly correlated with the endogenous explanatory variable it is instrumenting (i.e. PT accessibility or car unavailability). Secondly, the instrument must have a very low correlation with the residual error from the second stage regression (on employment). These two requirements are referred to as instrument relevance and instrument exogeneity.

We cannot test this second requirement, instrument exogeneity, other than appealing to economic intuition. Given a selected instrument (or instruments) we can however test for instrument relevance by comparing the OLS and 2SLS-IV estimates for employment to determine whether the differences are significant. If the estimates differ this implies there may be some degree of endogeneity and IV is appropriate. This is known as the Wu-Hausman test. An additional test known as the Sargan test uses over-identifying restrictions in a statistical model involving more than one instrument for each endogenous variable to test whether these instruments are truly exogenous.

Successful IV estimation often involves use of long time-lags of the instrumented variables as instruments in the (first stage) instrumenting regression. This is because it can be argued that these lagged values cannot have been influenced by the current level of the dependent variable (e.g. employment) and are thus exogenous. We were able to make use of this, as the dataset did include lagged measures of PT accessibility for 2009[5] and information from the 2001 Census on car unavailability. If there is endogeneity and it is not controlled for then

[5] Though the cross-section data did include 2007 accessibility measures we did find that, as for the panel data, these 2007 measures must have been created using a different methodology to subsequent years. Accessibility measures for 2008 were not available.

OLS estimates of the relationship may be biased, yielding parameters which do not accurately reflect the direction of causation.

3 DATA

3.1 Accessibility Indices

For measures of accessibility, we used DfT derived accessibility indicators (DfT, 2012) for journey times to employment areas calculated separately by public transport and by car. The public transport/walking based indicators primarily captures bus travel times as the main PT mode but also includes rail and other modes. The travel time indicators, by public and by private transport mode, are constructed by the DfT to measure the time taken for users to reach the nearest areas with large numbers of people in employment. These travel time indicators are then used to inform governments on public and private transport policy recommendations. The calculation of these travel times is rather complex and described in more detail in Johnson et al. (2014) and DfT (2012). The measures are essentially peak weighted average journey times to the nearest large employment area. As such they are a rather crude measure of potential employment, not based on actual commuting patterns and do not apply the more sophisticated spatially weighted employment accessibility approach used in some case studies. The measures do however offer a nationally comparable set of accessibility indices calculated on a consistent basis not readily available elsewhere.

For our purposes we are focusing on the nearest employment centre with above 5000 jobs[6,7]. Employment centres are determined using the number of jobs in a Lower Super Output Area (LSOA) with an average of roughly 1,500 residents and 650 households, made up of several output areas (OA) which are the smallest spatial areas used in the Census.

The timetable information is based on the National Public Transport Data Repository (NPTDR, www.nptdr.org.uk) – which is an annual snapshot for representative week of timetable based journey time information from public transport access points (e.g. bus stops) for England[8]. These data are then processed to create single public transport access point locations for each OA. It is assumed that people in an output area can use a number of possible access points within their MSOA.

Travel times are calculated for journeys between these access points and employment destinations and captured in a journey time matrix. For each of the ten quickest routes, the public transport times are calculated for 23 half hourly slots for incoming and outgoing trips. Each of the 46 travel times are then weighted by likelihood of travel (based on generic departure time profiles) to give a representative travel time based on likely patronage.

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[6] The results in this report are based on the 5000-plus travel area measures as we believe these are a better representation of concentrated areas of employment, and as such performed better in the estimates. These data were derived for us by the DfT during the project but the resulting delays gave us less time for the analysis. The inconsistency in the 2007 travel data remained in the 5000-plus dataset.

[7] We acknowledge, in particular, the help of Rachel Moyce from the DfT in co-ordinating the processing of this data.

[8] Including bus, tram, train, ferry, coach and rail and metro and walking (for short distances).

The following assumptions, outlined in Table 3-1, were used when calculating times on each route. The travel times estimated for each MSOA and LAD are population weighted versions of the derived OA values.

Table 3-1: Elements of Journey time measures

Journey time element	**Assumption**
Door to boarding public transport	Minimum time: 5 mins
Door to public transport stop/node	Maximum distance: 1.2 miles (24 mins)
Waiting time at bus stop/station/etc.	Based on frequency (maximum time: 20 mins)
Maximum interchanges	3
Interchange time	Minimum 10 mins

(Source: DfT (2012))

Another simplification is that these measures are not weighted to represent generalised journey time or able to be broken down to their component elements of walk, wait and in vehicle time to facilitate estimation of GJT.

Supplementary fare data were not available at required zonal level so unweighted travel time was our sole accessibility indicator.

Car journeys are assumed to start at the population centroid. The journey connection is made directly from the road and footpath network to the nearest large employment centre (with 5000 or more jobs) as specified by the co-ordinates. A similar approach to that used for public transport is adopted by building a MSOA level matrix across England and infilling this to each OA using the local road network.

3.2 Dependent variable

Dependent variables were based on the employment level for 16-64 year olds available from NOMIS for the 2011 Census (www.nomisweb.co.uk) at the MSOA level. We also experimented with the use of employment rate as the dependent variable but focus on employment level results here. This is because estimation of the value of labour supply impacts through WebTAG is based on exchequer impacts of absolute changes in numbers employed.

3.3 Rural/Urban Stratification

An important element of our analysis was to understand whether the sensitivity of employment to bus travel time varied by area type. In order to undertake this segmentation of area types we referred to the typology outlined in the Defra Classification of Local Authority Districts and Unitary Authorities in England (DEFRA, 2009). Table 3-2 shows the DEFRA classifications and our final grouping.

Table 3-2: Rural and Urban Stratifications used in analysis

DEFRA Classification	DEFRA Definition	Final Stratification
Major Urban	100k people or 50 percent of their population in an urban area with a population of more than 750,000	Split into Dense Urban (i.e. Metropolitan) and London
Large Urban	50k people or 50 percent of their population in one of 17 urban areas with a population between 250,000 and 750,000	Other Urban
Other Urban	<37,000 people or less than 26 percent of their population in rural settlements and larger market towns	
Significant Rural	More than 37,000 people and more than 26 percent of their population in rural settlements and larger market towns	Rural
Rural-50	districts with at least 50 percent but less than 80 percent of their population in rural settlements and larger market towns	
Rural-80	districts with at least 80 percent of their population in rural settlements and larger market towns; there are 73 districts in this group	

3.4 Other co-variates

This data set allows us to investigate the relationship between spatial differences in bus (and car) accessibility and differences in employment rates, controlling for other localised factors such as population level, density and the profile of the population in terms of the percentage of car unavailability, males, ethnic minorities, and those with English as a first language[9].

We capture industrial structure by using a binary dummy variable to represent the industrial grouping which has the highest relative concentration (i.e. the highest percentage uplift relative to the national average employment share of that sector). These groupings are based on the 2007 Standard Industrial Classification classifications from the census which we have categorised as Manufacturing, Retail, Business services, Professional, Public and Service sectors10. These measures attempt to control for the structure of employment in each area. Some more deprived areas are reliant on public sector employment or may have higher concentrations of employment in retail or service sectors.

[9] Other variables experimented with included degree and no qualifications, lone parents, multiple deprivation scores and social class. We had to omit these variables because they were highly correlated (0.8 or higher) with at least one of the variables we did retain and could lead to counter-intuitive signs on estimated coefficients. Ethnicity was dropped as insignificant.

[10] Manufacturing comprised SIC groups C (Manufacturing) and F (Construction); Retail is represented by group G (Wholesale and retail trade; repair of motor vehicles and motor cycles); Business services comprised SIC groups J (Information and communication) and K (Financial and insurance activities); Professional is represented by group M (Professional, scientific and technical activities)· Public comprised SIC groups O (Public administration and defence; compulsory social security), P (Education)·,Q (Human health and social work activities)

Table 3-3: Descriptive Statistics

		Area types							
		London		Dense Urban Areas		Other Urban Areas		Rural	
Description	Variable name	Coeff	Std. Error	Coeff	Std. Error	Coeff	Std. Error	Coeff	Std. Error
Employed16to64	Employed	3977	28.394	3317	21.691	3591	19.768	3582	17.234
Bus travel times to employment centres	Bus T.T.	21.12	0.346	21.95	0.284	25.00	0.40	50.30	0.575
Car travel times to employment centres	Car T.T.	8.97	0.175	7.80	0.089	8.7	0.181	16.08	0.213
Population (16-64)	Population	5744	36.735	4922	33.368	5118	28.782	4778	21.742
Population Density	PopDensity	83.8	1.564	34.8	0.592	33.8	0.574	12.6	0.297
Manufacturing dummy	Dummy_manuf	0.01	0.002	0.31	0.013	0.31	0.011	0.31	0.009
Retail dummy	Dummy_retail	0.04	0.006	0.13	0.009	0.15	0.008	0.09	0.006
Business dummy	Dummy_business	0.39	0.016	0.09	0.008	0.19	0.009	0.12	0.006
Professional dummy	Dummy_profess	0.28	0.015	0.12	0.009	0.05	0.005	0.21	0.008
Public dummy	Dummy_public	0.03	0.006	0.18	0.011	0.15	0.008	0.13	0.007
Service dummy	Dummy_service	0.25	0.014	0.18	0.011	0.16	0.008	0.15	0.007
Proportion of English first language speakers	Ratio(EFL)	0.78	0.004	0.93	0.002	0.94	0.002	0.97	0.001
Proportion of males	Ratio(Male)	0.54	0.001	0.53	0.001	0.53	0.000	0.53	0.000
Proportion of non car available households	Ratio(NCA)	0.40	0.006	0.30	0.004	0.25	0.003	0.17	0.002
Observations		951		1268		1876		2540	

The descriptives in **Table 3-3** highlight the underlying differences between the four area types. Car and public transport journey times to large employment centres are roughly double in rural areas compared to other areas. Population densities are highest in London and lowest in the Rural areas. London has a higher concentration of business and professional sector employment and with urban areas having higher concentration of retail and public sector occupations. London has a lower concentration of manufacturing jobs. London has the highest level of car unavailability (40%) and rural areas have the lowest (17%). This might be because people in denser urban areas are less likely to need a car, or more likely to be put off owning a car due to parking issues and congestion. London has the lowest proportion of those with English as first language.

4 RESULTS

Table 4-1 reports the results of the OLS regression (with Fixed Effects for LADs) on the natural log of employment levels. All models report high R-squared statistics indicating good overall model fit. Due to this functional form, coefficients on bus and car travel times can be interpreted as elasticities.

Table 4-1: **Results for models of Employment level by area type**

	London		Dense Urban Areas		Other Urban Areas		Rural	
Employment	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
ln(Bus T.T.)	-0.025**	-3.4	-0.028**	-4.0	-0.016**	-2.3	-0.012**	-3.6
ln(Car T.T.)	0.024**	3.2	0.010	1.1	0.011	1.2	0.009**	2.4
ln(Population)	1.082**	84.1	0.984**	94.8	0.950**	91.0	1.004**	199.7
ln(PopDensity)	0.024**	5.2	0.012**	3.6	0.021**	7.4	0.013**	11.7
Dummy_retail	-0.003	-0.1	-0.020**	-2.6	-0.024**	-3.2	-0.008*	-1.9
Dummy_business	0.029	0.0	0.012	1.2	0.005	0.6	0.010*	1.9
Dummy_profess	0.054*	1.9	0.004	0.5	-0.053**	-4.6	-0.009**	-2.3
Dummy_public	0.002	0.1	0.009	1.2	-0.003	-0.4	0.003	0.9
Dummy_service	-0.011	-0.4	-0.043**	-4.8	-0.058**	-6.8	-0.022**	-5.3
Ratio(EFL)	0.456**	9.9	0.701**	12.4	0.389**	7.0	0.128**	2.8
Ratio(Male)	0.298**	2.4	0.011	0.1	0.340**	2.2	-0.198**	-2.5
Ratio(NCA)	-0.295**	-9.9	-0.654**	-27.4	-0.710**	-26.4	-0.586**	-28.9
Constant	-1.591**	-10.5	-0.688**	-4.3	-0.322**	-2.0	-0.243**	-2.9
R-squared (within)	0.91		0.90		0.85		0.95	
R-squared (overall)	0.89		0.89		0.91		0.94	
Groups (FE Constants)	43		41		102		159	
Observations	951		1268		1876		2540	

** - significant at 5%; * - significant at 10%.

The elasticity of employment with respect to bus travel times are consistent across the areas in that they have both the expected negative sign and are significant at the 5% level. These coefficients indicate that a 10% reduction in bus travel times is associated with, all else equal, a 0.13-0.3% increase in employment[11]. Higher values are found in London and dense urban areas with the lowest value in rural areas. This is to be expected given the larger mode share and relative effectiveness of public transport (compared to private modes) in denser urban areas.

The coefficients on car travel times are positive but only significant for London and Rural areas. Their interpretation is not straightforward but perhaps they are an indication that higher employment areas are associated with longer car commutes. Also they are an indication that car travel times are not a barrier to finding employment. Over 88% of observations of car access times were under 20 minutes; a commute time which would deter few car drivers. Also it highlights shortcomings with the car accessibility measure. There is not much variation in the access times with around 15% of the observations recorded at the minimum of 5 minutes. There is a much larger range of public transport accessibility times as evidenced by the standard errors in **Table 3-3**.

[11] For the lower bound rural areas, this is derived by 0.9^-0.012=0.13%; for the upper bound dense urban areas, this is derived by 0.9^-0.028=0.30%.

The proportion of those with car unavailability, Ratio(NCA), has a significant and negative impact on employment. This variable is highly correlated with the socio economic makeup of an area, with higher social class more likely to have access to a car. This variable also varies systematically with urban density.

The results for the other socio-economic covariates are broadly as expected. Employment is positively and significantly related to population size and density. Larger and denser areas typically have better access to employment, particularly by public transport, all else equal, given the larger base loads of passengers. The proportion of those with English as a first language has a significant and positive impact on employment.

The industrial structure dummies suggest employment is higher in areas more specialised in retail and services compared to manufacturing (the omitted base). Results for other industries were less clear (e.g. the negative impact of more concentrated professional sectors in other urban and rural areas) or significant (e.g. public sector).

Table 4-2: **Comparative Analysis**

Variable	London	Dense Urban Areas	Other Urban Areas	Rural
A. Bus TT Elasticity	-0.025	-0.028	-0.016	-0.012
B. NCA Elasticity	-0.07	-0.142	-0.141	-0.0758
Ratio (A/B)	**2.8**	**5.1**	**8.8**	**6.3**

For more perspective on the results we re-ran the models to derive elasticities for the NCA variable[12]. These figures are compared with the elasticity of employment with respect to bus travel times derived from the models in Table 4-1 and shown in Table 4-2 along with the ratio of the two figures for each area. The figures suggest that if we introduced a policy which reduced the proportion of households with no car availability by 1%, e.g. from 50% to 49.5%, (through cheaper fuel duty or VED for example) this would increase employment by 0.07% in London and up to 0.14% in Urban Areas. To have an equivalent employment impact we would have to reduce bus travel times by 2.8% in London, 5.1% in Dense Urban Areas, 8.8% in Other Urban Areas and 6.3% in Rural Areas. It is clear that employment is far more sensitive to changes in car availability than bus travel times, particularly outside London and dense urban areas. How costly it is to change car availability compared to Bus travel times is out of scope for this paper; however it does suggest the public transport investments make more sense in urban areas in terms of employment impacts.

Results for employment rate[13] are reported in Table 7-1 in the appendix. With the exception of population, these are very similar in terms of sign and robustness although interpretation of the parameters as elasticities is not as straightforward given the log terms represent proportional impacts on a rate (so a parameter of -0.016 on PT times in London implies a 10% reduction in PT times would lead to an uplift of a factor of 1.017 in the employment rate).

[12] We replaced the NCA proportion with the log of NCA percentage in the regressions.

[13] The official employment rate is calculated as E/(E+U+I), where E represents the numbers in employment, U unemployment and I represents the numbers economically inactive.

The full IV results are not reported here but summary statistics are reported in the appendix Table 7-2. These results yielded some interesting findings. We found little evidence that either public transport travel time or car unavailability were endogenous suggesting a causal link between accessibility and employment. The exceptions were car unavailability in London and public transport travel times in other urban areas. In all other cases we found we could not reject the null hypothesis that car unavailability and accessibility variables are exogenous at the 5% level of significance, ie there was no evidence of an endogenous relationship between these variables and employment. When instrumented by 2001 car unavailability, we found both the car unavailability and public transport coefficients increased in absolute value suggesting that they are not biased upwards in the straightforward OLS approach. In the London case, including both instruments simultaneously led to a rejection of the null hypothesis that the over-identifying restrictions are valid (Sargan test), suggesting the instruments are not exogenous. In the case of 'other' urban areas we found that including both instruments led to a non-rejection of the null (ie suggesting that the instruments are exogenous).

5 CONCLUSIONS

Public transport plays an important role in facilitating access to the labour market for workers in Britain but there is little empirical evidence as to the extent of its impact. Here we have analysed a cross-sectional dataset of travel accessibility indicators, labour market indicators and socio demographic information to estimate the impact of differences in public transport (PT) accessibility on local labour market outcomes. For London and dense urban areas, PT accessibility might well include trains and trams but for other urban areas and rural areas this could reasonably be interpreted as bus accessibility.

As expected, we found a statistically significant and negative relationship between public transport travel time and employment, which varies in magnitude by urban type. This suggests a linkage between variation in the quality of the public transport network and the level of employment at a local level. Our models appear plausible in terms of signs and magnitudes for all estimated coefficients. The results suggest a difference of 10% in bus journey times between areas would be associated to 0.13-0.3% difference in employment depending on area type with higher values in more urbanised areas which typically have more developed public transport networks and higher utilisation.

In terms of a link to policy, the fixed effects approach suggest an interpretation based on the impact of differences in travel times on employment 'within' local authorities of a particular urban type. An improvement in PT services, such as through service level increases or journey time reductions from prioritisation schemes, in one MSOA area would, by implication, suggest there may be a consequent improvement in employment in that area in the long run. The employment effects will be larger in denser urban areas. The reported elasticities do not tell us what would happen if all travel times were changed across all areas within an LAD or indeed across all areas as there would be an additional 'between' group effect which is not estimable from our approach.

More broadly our results suggest that wider economic impacts are not the preserve of large scale capital investments (eg HS2) but are relevant also any policies which improve accessibility such as increased revenue support for bus services promoting better service levels. Such employment effects may also have a distributional dimension as they impact more on the lower paid who rely heavily on the bus for access to employment compared to the larger scale investments which favour higher paid long distance commuters and business travellers. These findings add to the limited existing evidence base in this field within the spirit of the current WebTAG framework.

Our findings are likely to be conservative given that no account is taken of second round effects of improved urban public transport on congestion levels for both public and private transport users.

We found little evidence of endogeneity between employment and car unavailability and public transport travel times. The IV results actually suggested that the coefficients on public transport accessibility and car unavailability were underestimated in OLS. Given the lack of statistical need and the inherent dangers in using IV approaches, we prefer the more conservative OLS estimates. We accept limitations in our approach, particularly given the short lags we have used and the aggregate nature of the analysis – there is more work to be done in this area to further establish the extent of the causal relationship between public transport accessibility and employment in Britain.

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7 APPENDIX

Table 7-1: Results of models by area type with employment rate as dependent variable

	London		Dense Urban Areas		Other Urban Areas		Rural	
Employment rate	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
ln(Bus T.T.)	-0.016	-3.3	-0.019	-4.7	-0.012	-3.1	-0.010	-4.3
ln(Car T.T.)	0.016	3.2	0.007	1.2	0.008	1.6	0.006	2.6
ln(Population)	0.055	6.5	-0.001	-0.1	-0.020	-3.3	0.006	2.0
ln(PopDensity)	0.017	5.6	0.007	3.7	0.013	7.7	0.009	12.8
Dummy_retail	0.001	0.0	-0.017	-4.0	-0.017	-3.9	-0.006	-2.2
Dummy_business	0.043	2.3	0.010	1.8	0.007	1.4	0.007	2.3
Dummy_profess	0.039	2.1	0.005	1.0	-0.032	-4.8	-0.005	-2.2
Dummy_public	0.003	0.2	0.004	0.8	-0.003	-0.7	0.002	1.0
Dummy_service	-0.002	-0.1	-0.024	-4.7	-0.034	-6.9	-0.013	-4.8
Ratio(EFL)	0.327	10.8	0.375	11.7	0.238	7.3	0.066	2.3
Ratio(Male)	0.242	3.0	-0.064	-0.8	0.222	2.5	-0.126	-2.5
Ratio(NCA)	-0.195	-9.9	-0.433	-32.0	-0.477	-30.5	-0.418	-31.8
Constant	-0.176	-1.8	0.528	5.9	0.646	7.0	0.775	14.2
R-squared (within)	0.55		0.80		0.60		0.45	
R-squared (overall)	0.56		0.81		0.72		0.49	
Groups (FE Constants)	43		41		102		159	
Observations	951		1268		1876		2540	

Table 7-2: Diagnostics from IV regression models.

Area type	Instrumenting for	Instrumenting with	Wu_Hausman chi_squared statistic	P value	H0: Variables are exogenous
London	ln(Bus T.T. $_{2011}$)	ln(Bus T.T $_{2009}$)	0.1359	0.7123	Don't reject
	Ratio(NCA $_{2011}$)	Ratio(NCA $_{2001}$)	56.8720	0.0000	Reject
Dense Urban Areas	ln(Bus T.T. $_{2011}$)	ln(Bus T.T $_{2009}$)	2.4986	0.1139	Don't reject
	Ratio(NCA $_{2011}$)	Ratio(NCA $_{2001}$)	0.0010	0.9746	Don't reject
Other Urban Areas	ln(Bus T.T. $_{2011}$)	ln(Bus T.T $_{2009}$)	8.3269	0.0039	Reject
	Ratio(NCA $_{2011}$)	Ratio(NCA $_{2001}$)	1.4533	0.2280	Don't reject
Rural	ln(Bus T.T. $_{2011}$)	ln(Bus T.T $_{2009}$)	1.6617	0.1974	Don't reject
	Ratio(NCA $_{2011}$)	Ratio(NCA $_{2001}$)	0.5522	0.4574	Don't reject