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# Does transport help people to gain employment? A systematic review and meta-analysis of the empirical evidence

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# Does transport help people to gain employment? A systematic review and meta-analysis of the empirical evidence


## Abstract

The role of transport in providing access to employment has received considerable attention. Since transport policies may be motivated by assumed effects on employment probability outcomes, it is important to establish the nature of the relationship between transport and employment outcomes. While the majority of the empirical evidence suggests a positive association, it is not conclusive or consistent and often shows mixed results. To address this confusion, our study has systematically reviewed this evidence base and synthesised it through meta-analysis.

We first identified 93 studies that quantitatively assessed the impact of transport on employment outcomes. By systematically merging the empirical evidence, this study establishes a positive association between transport and employment outcomes, with varying effects for four identified categories of transport measures (or combinations thereof): car ownership, public transport access, commute times, and job accessibility levels. This positive association persists in studies that control for endogeneity between transport and employment, but a larger evidence base is needed to establish a more robust relationship, in particular for cities and smaller (rural) areas outside the US-context and with regard to public transport.

We then selected 20 methodologically comparable studies for inclusion in the meta-analysis. Our meta-regression models clearly demonstrate that car ownership significantly increases individual employment probabilities, in particular among welfare recipients. Young drivers benefit from access to household cars when these are not in use by their parents, and they are more sensitive to the time and cost implications of longer commutes. While our systematic review suggests that better access to public transport and higher levels of job accessibility increases employment probabilities, meta-regression analysis requires more consistent transport measures. The findings in this study are important for policymakers in that they imply that job seekers may benefit from public policies targeted at improving their access to public transport, in particular for people without access to cars and in areas with fewer job opportunities.



Keywords: transport, car, commute, accessibility, meta-analysis, employment


## 1. Introduction

Transport has been associated with improved employment probability outcomes as it provides people with greater access to spatially dispersed job opportunities. Following the seminal work of Kain (1968) on the Spatial Mismatch Hypothesis, who argued that a major source accounting for inner-city unemployment in the US was to be found in poor access to job opportunities, a large body of studies in US metropolitan areas have ensued. More recently, some studies have also evaluated this relationship in EU cities (Ihlanfeldt and Sjoquist, 1998, Gobillon et al., 2007). However, while most studies largely confirm the positive effects of transport on employment probability outcomes, some find insignificant or even negative outcomes, implying that transport policies targeted at improving people's employment probabilities may not be effective as a policy instrument in all cases.

However, the mixed empirical results of previous studies may also arise from the use of different transport measures and employment outcomes, which are, thereby, difficult to compare in a meaningful and consistently measurable way. Most studies relate individual employment probabilities or employment rates to a measure of transport access – i.e. with car ownership, public transport access, commute times, or job accessibility measures typically used as the key indicator of transport supply. Disparities may further arise from limitations in the underlying datasets and methodologies (Gobillon et al., 2007). Additionally, studies typically focus on US metropolitan areas, and it is unclear whether the statistical relationships would hold in less car-dependent environments (such as European cities) or in smaller travel-to-work zones, where travel times and distances are shorter (Ihlanfeldt, 2006).

A further limitation of many studies lies in their lack of consideration of potential endogeneity (non-causality) between transport and employment probability outcomes: for example, access to a car is likely to increase people's employment probabilities, while a job also provides the financial means for a car, which may bias study results. Linking employment outcomes to transport further raises the issue of residential endogeneity because of the simultaneity between an individual's employment outcome and residential location decision (Glaeser, 1996). Studies that do not control for endogeneity, therefore, establish an association rather than causality between transport and employment probability outcomes.

It is important to establish the exact nature of the relationship between transport and employment outcomes, since transport policies may be motivated by assumed effects on employment outcomes, as well as to identify the causes underlying the mixed empirical results. The aim of this reported study has therefore been to: (i) systematically review all studies that have quantitatively assessed[1] the relationship between transport and employment probability outcomes, and (ii) synthesize the identified studies through a meta-analysis to produce general effect sizes of the relationship between transport and employment probability outcomes and to determine the sources of variation in the mixed empirical results.

Within the transport domain, meta-analyses have previously been conducted to establish the relationship between productivity gains and urban agglomeration economies, with transport being implicitly incorporated (Melo et al., 2009), the productivity effects of transport infrastructure (Melo et al., 2013), and effects of public transport infrastructure on regional growth (Elburz et al., 2017). To date, however, no meta-analysis has established the specific relationship between transport access and employment probability outcomes. In this study, we focus on the empirical evidence that quantitatively assesses this relationship using individualized employment probability metrics. This allows us to estimate the overall effect sizes of transport access on employment probability outcomes, which, in turn, can help to identify transport policies with the greatest effect on employment uptake.

In our meta-analysis, we are principally interpreting individual employment impacts as based on labour supply side effects arising from incremental changes in accessibility. Better accessibility to employment opportunities will hypothetically reduce the amount of time required to find work both in terms of expanding job search horizons and increasing the offered wage of a given job, net of transport cost (i.e. reducing their reservation wage) and, thereby, hypothetically increase the likelihood of applying for and accepting such work. The underlying data for our models are derived from cross-sectional studies, which compare employment outcomes across different areas (i.e. rather than before and after new transport interventions). These studies typically looked at the impact on individual's employment probabilities of accessibility, measured through differences in car ownership or mean neighbourhood commute times by public transport or car. There is a labour demand dimension to improving accessibility which plays out principally through better connectivity promoting agglomeration (see Banister and Berechman (2001) for discussion), which could be

[1] Qualitative studies could provide important insights into perceived transport barriers to employment, however, these were outside the scope of our study because they do not quantify this relationship.

amplified through land use change, thus increasing productivity and the demand for labour, however, this issue is outside the scope of this paper.

## 2. Methodology

We systematically reviewed and synthesized all available evidence that has quantitatively assessed the relationship between transport access and employment probability outcomes. The review was conducted up to 2019, and involved identification of all relevant studies using keyword combinations related to 'transport', 'impact' and 'employment'[2] in the publication title, abstract and keywords of studies. The search engines of Science Direct, Web of Science and Google Scholar were used. Additionally, websites of specialist institutes such as Centre for Economic Policy Research, London School of Economics and the grey literature (including reports, conference proceedings and dissertations) were searched separately. The searches were performed without restrictions on publication date, status or language of publication. In addition to the database searches, the recent synthesis report Transport Review by the WhatWorksCentre (2015) and the reference lists of all included studies and literature in the author's databases were screened for relevant studies.

In total, 2958[3] unique studies were identified, from which 118 studies were selected that directly related transport access to individual employment outcomes. The excluded studies were found either to be unrelated to transport or employment outcomes, or used qualitative methods that did not quantify this relationship. The full text was obtained for the 118 identified studies and reviewed, after which we identified 93 studies that quantitatively assessed the impact of transport on employment outcomes. Fifteen studies were excluded for not providing quantitative model estimations for the impact of transport on employment outcomes and another ten studies were excluded as their measures did not incorporate a transport component (e.g. these studies used job ratio or job density measures).

We manually extracted data from the 93 identified studies using a predefined data template including: study sample size; characteristics and geographical location; transport and employment measures used; cross-sectional or longitudinal datasets; econometric model type and controls for endogeneity (e.g. subsamples, IV-approach); and effect sizes (coefficients, standard errors, and p-values)[4].

As hypothesised, there was considerable variation in transport measures and employment outcomes. We identified four categories of transport measures (or combinations thereof) that were used in the studies: car ownership, public transport access, commute times and job accessibility levels. The studies typically assessed individual employment probabilities or neighbourhood employment rates, as discussed in section 3. To gain an understanding of the extent to which transport affects employment outcomes and to determine the sources of variation in the mixed empirical results, we next synthesized the methodologically comparable empirical evidence through a meta-analysis.

### *2.1 Meta-analysis*

Meta-analysis is a systematic framework that allows estimation of effect sizes of relationships, in our case between transport and employment outcomes, based on merging of common variables in datasets taken from different individual studies (Boland et al., 2014, Littell et al., 2008, Borenstein et al., 2009). As this requires to compare 'like with like' we confined our meta-analysis to studies that assessed individual employment probabilities (being employed as opposed to being not employed)

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[2] Transport keywords: transport*, infrastructure, travel*, commut*, road, highway, motorway, car, transit, rail, tram, bus, metro, subway, bicycle, walk; Relationship keywords: relation*, impact, caus*, eval*, experiment, affect*, effect*, link*, case*; and Employment keywords: employment, job, labour, productivity, economic activity. Keywords 'access' and 'work' were not used as being found too general.

[3] In total 2392 studies from online searches; 189 studies from WWC report; and 377 studies from own libraries.

[4] The citation database is available through: https://doi.org/10.5518/762

using binomial logit models. Of the 93 identified studies, 20 comparable studies were included in the meta-analysis that all used binomial logit models to explain individual employment probabilities resulting from car ownership (12) or commute time (8). These studies yielded similar effect sizes, which is a requirement for meta-analysis (Boland et al., 2014). The various public transport access and job accessibility measures used in studies were found incompatible with each other and thus were unsuitable for a meta-regression. We excluded studies using multinomial logit, probit or Tobit models due to their different functional form yielding incomparable coefficients. We also excluded studies focussing on employment rates as these cannot be directly compared with individual employment probabilities.

As meta-analysis typically involves a regression-based approach (Waldorf and Byun, 2005), we used the reported coefficients (i.e. log-odds ratios) and standard errors related to transport measures as effect sizes for our meta-regressions. Since the studies varied in terms of sample sizes and significance of the estimated effects, we followed the 'gold standard' in meta-analysis and calculated weights based on the 'inverse variance' of the squared standard error, which minimizes the variance of the average effect size estimates and assigns the greatest weight to the most precise estimates of individual studies (Borenstein et al., 2009, Littell et al., 2008). We then conducted a random-effects regression using the inversely weighted mean effect sizes [5]. A fixed-effects model was deemed inappropriate as it assumes that all included studies share a common effect size, while we expect similar but not per se identical effect sizes due to different socioeconomic covariates (Borenstein et al., 2009).

To compare and interpret the estimated effects we used 'odds-ratios', which describe the ratio of the probability of an event occurring relative to the probability of the event not occurring (Boland et al., 2014). For example, if the odds of being employed relative to being not employed are higher for car owners than those without a car, the odds ratio would be higher than 1, while the opposite effect would yield an odds ratio less than one. A defining characteristic of binomial logit models is that the coefficients are log-odds ratios, which could therefore easily be transformed into odds-ratios by taking their exponential. While employment elasticities are easier to interpret, the logit functional form used by constituent papers in our meta-regression does not allow for the derivation of constant elasticities of employment and most studies did not report elasticities or the required descriptive statistics for all (sub)models by which to derive them.

Both significant and insignificant coefficients from individual studies were included in the meta-analyses, as dropping the insignificant observations could have biased the effect sizes by over- or underestimating the impact of transport on employment outcomes. This is a standard approach in meta-analysis (see e.g. (Melo et al., 2009, Ewing and Cervero, 2010)). In accordance with Ewing and Cervero (2010), we included both published and unpublished studies in our meta-analysis, as publication bias may inflate the results estimated by the meta-analysis.

Since the variation between the studies in terms of transport indicators, samples, and strategies to account for endogeneity are likely to have different impacts on employment outcomes, we also conducted random-effects generalized least squares (GLS) meta-regressions with study-specific covariates for our two meta-analyses samples, based on the log odds (coefficients) of the reported individual employment models and dummy variables for four aspects of each study: (1) definition of the transport indicator (e.g. car ownership, one/multiple household cars, car commute times); (2) study samples used (e.g. youth (Black, Hispanic, white), women, welfare recipients); (3) treatment of residential endogeneity (e.g. youth living at home); or (4) treatment of transport endogeneity (e.g. an

[5] Following Borenstein et al. (2007), under the random-effects model the weight assigned to each study is $W_i = 1/V_i$, where $V_i$ is the within-study variance for study $i$ plus the between-studies variance (sum squared deviations of each study from the combined mean), tau-squared.

instrumental variable (IV) approach[6]). Since all studies included individual, household, and neighbourhood controls, we did not include dummy variables to control for these additional variables, as they were already inherent within the source models.

## 3. Systematic review of literature on transport and employment outcomes

This section discusses the results of our systematic review, based on a categorisation of the studies by their transport measures and employment outcomes: individual or household car ownership measures in section 3.1, public transport measures in section 3.2, commute time measures in section 3.3, and job accessibility measures in section 3.4, followed by conclusions in section 3.5.

### *3.1 Studies using individual or household car ownership measures*

We identified 42 studies that assessed the association between access to a car and individual employment probabilities, in mainly US metropolitan areas. Eight cross-sectional studies found a positive association between individual car ownership and employment probabilities among low-income and low-educated groups (Rice, 2001, Kawabata, 2002, Kawabata, 2003, Lucas, 2003, Garasky et al., 2006, Stoll, 2005) and (female) welfare recipients (Ong, 1996, Sanchez et al., 2004), especially in more car-dependent areas. Three studies further found that household car ownership increased employment probabilities of (low-skilled) youth (Painter et al., 2007), in particular when they had access to multiple household cars (Bauder and Perle, 1999, Perle et al., 2002). Similar associations have been found for the Czech Republic (Marada and Květoň, 2016) and among aborigines in rural Taiwan (Lin et al., 2014).

While access to a private car is associated with increased employment probabilities, Ong and Houston (2002), found no statistically significant effect on employment for welfare dependent women who were unable to borrow a car. Other studies did find that a driver's license or higher numbers of household cars increased employment probabilities (Yi, 2006, Smart and Klein, 2015), with similar associations being found in the Barcelona and Madrid metropolitan areas (Matas et al., 2010, Di Paolo et al., 2014). In France, Cavaco and Lesueur (2004) further showed that car access was related to shorter unemployment durations. These studies thus suggest that individual and household car ownership increase individual employment probabilities, however, endogeneity was not controlled for, i.e. did the car precede or follow the job?

Three US studies controlled for endogeneity by using an instrumental variable (IV) approach to predict household car ownership and also found an increase in employment probabilities of single welfare women (Ong, 2002, Bansak et al., 2010) and male and female labour force participation (Thompson, 2001). Four other US studies used longitudinal datasets, assuming an exogenous relationship if car ownership preceded employment, and typically found car ownership associated with shorter unemployment durations (Holzer et al., 1994, Sullivan, 2003, Dawkins et al., 2005, Johnson, 2006). Twelve US studies utilized longitudinal welfare data, also showing positive associations between (gained) car ownership and welfare-to-work transitions (Blumenberg, 2008, Cervero et al., 2002, Cervero and Tsai, 2003, Shen and Sanchez, 2005, Gurley and Bruce, 2005, Sandoval et al., 2011, Alam, 2009, Blumenberg and Pierce, 2017) or for having a driver's license (Bania et al., 2003), and between car access and job retention (Thakuriah and Metaxatos, 2000). Alternatively Danziger et al. (2000), showed that having no car or driver's license decreased weekly worked hours of single welfare mothers. O'Connell et al. (2012) found similar associations for male

[6] An IV-approach uses a third variable (Z) correlated with employment only through the applied measure of transport access to control for endogeneity between employment probability outcomes and transport access.

welfare recipients in Ireland. However, car ownership status between baseline and follow-up surveys is often unregistered, making it uncertain whether the car preceded the job. Four US studies combined longitudinal datasets with an IV-approach and also found that car ownership increased employment probabilities, in particular among low-skilled workers (Raphael et al., 2001, Raphael and Rice, 2002) and single welfare mothers (Baum, 2009), and increased the labour supply of low-income households (Bee, 2009). For France, Le Gallo et al. (2017) further found that randomly assigned vouchers for driving lessons among young unemployed slightly increased their long-term employment prospects, but skills-mismatches were more important.

We further identified two cross-sectional studies that established positive associations between cars per capita and employment rates in the US (Gao et al., 2008) and in the Czech Republic (Marada and Květoň, 2016). This association persists in studies by Sanchez (1999) and Ong and Miller (2005) that used an IV-approach to predict cars per capita. However, due to their reliance on zonal-level data, these studies may suffer from aggregation biases.

### *3.2 Studies using public transport access measures*

Seventeen studies have assessed the association between public transport access and employment probabilities. Three US studies found small positive effects of access to a higher number of bus stops and stations within a certain radius (Ong and Houston, 2002, Yi, 2006) or higher public transport route densities (Rice, 2001), particularly among those without cars, but not for distances to bus stops (Yi, 2006). Sanchez (1999) found a positive association between hours worked and shorter distances to bus and rail stops, but not for morning service frequencies at the nearest stop. A later study by Sanchez et al. (2004) also found no association between evening service frequencies and employment probabilities of welfare recipients, which may indicate that public transport offered poor access to suitable job at the required times. This seems reconfirmed by studies that found a negative association between public transport dependence and employment probabilities among welfare recipients (Blumenberg, 2002), with labour force participation of non-white workers (Cooke, 1997), or with having paid work among non-white workers (Taylor and Ong, 1995). O'Connell et al. (2012) used longitudinal data but found no effect of residing near public transport stops among Irish welfare recipients. However, once again, these studies often have not adequately controlled for endogeneity.

Four longitudinal studies controlled for endogeneity through policy-induced rail infrastructure extensions, which connected disadvantaged neighbourhoods with employment locations, typically finding increased individual employment probabilities in the US (Holzer et al., 2003), in Copenhagen (Rotger and Nielsen, 2015), Sweden (Aslund et al., 2015), and in France (Sari, 2015). However, it remains unclear if the siting of the rail infrastructure is codetermined with economic activity, which is required to establish exogeneity (Duranton and Turner, 2012). Tyndall (2017) therefore used a ‘natural shock’-based closure of a train line in New York and found increased unemployment probabilities in adjacent neighbourhoods, particularly among minority populations without cars. A later study by Tyndall (2019) used an IV-approach and showed that newly opened light rail stations had improved neighbourhood employment rates in US-metropolitan areas, while displacing low-skilled workers to isolated neighbourhoods. The group displacement effects of large public transport developments have recently gained much attention (see also (Padeiro et al., 2019)).

Two further longitudinal studies found strongly increased (short-run) employment probabilities among young unemployed in urban low-wage labour markets, especially for those with poor job access, following randomly assigned fee-reducing public transport cards in Washington (Phillips, 2014) and from non-fungible public transport subsidies in Addis Ababa (Franklin, 2015). Lower public transport travel costs may thus also improve job access and, in turn, increase employment probabilities.

### *3.3 Studies using commute time measures*

We identified 22 studies in mainly US metropolitan areas that have examined the association between mean neighbourhood car or public transport commute times and employment probability outcomes. Two cross-sectional studies found higher mean commute times associated with decreased individual employment probabilities among low-wage workers (Thakuriah, 2011) and low-educated women (Thompson, 1997). Cooke (1997) further found lower commute times related to higher labour force participation, but only for married mothers. This suggests that (female) workers may adjust their labour supply when job access increases because of lower commute times. Sanchez (1999), however, found a positive association between commute times and annual weeks worked, especially when including white people; since their annual weeks worked were higher than for non-whites, this might indicate that commute times rise with (improved) employment. Again, these studies did not control for endogeneity.

Ten cross-sectional studies in various US metropolitan areas used samples of (low-skilled) youth residing with their parents, as their residential location is more plausibly exogenous. These studies typically found higher mean commute times associated with lower employment rates (Ellwood, 1986) and decreased individual employment probabilities, especially among public transport captives (Ihlanfeldt and Sjoquist, 1990, Ihlanfeldt and Sjoquist, 1991, Ihlanfeldt, 1992, Ihlanfeldt, 1993, Holloway, 1996, O'Regan and Quigley, 1991, O'Regan and Quigley, 1996, Bauder and Perle, 1999, Perle et al., 2002). Four studies used an IV-approach to control for endogeneity, finding that lower mean (gravity-based) commute times increased individual employment probabilities (Berechman and Paaswell, 2001, Ozbay et al., 2006), and explained interracial youth employment differences (O'Regan and Quigley, 1998). Johnson et al. (2017) also found in England that lower public transport travel times to employment centres was related to higher employment levels.

Two longitudinal studies further found lower mean commute times associated with shorter (youth) unemployment durations in the US (Holzer et al., 1994) and in France (Cavaco and Lesueur, 2004). For Great Britain, Sanchis-Guarner (2013) also found that higher mean commute times decreased (female) labour supply. Taylor and Ong (1995), on the other hand, focussed on long-term residents in various US metropolitan areas and found that workers with short commute times had more often given up their jobs, because of a dispersion of (low-skilled) jobs. Decreased job access due to longer commute times thus may reduce employment probability outcomes.

### *3.4 Studies using car or public transport job accessibility measures*

We identified 33 studies that assessed the relationship between car or public transport job accessibility measures - typically based on the number of jobs reachable within 30/ 45 minutes' travel time or within a weighted travel time from each neighbourhood - and individual employment probabilities. Three studies in US metropolitan areas found positive associations for higher ratios of public transport to car job accessibility (Kawabata, 2002, Kawabata, 2003) and better bus job accessibility (Yi, 2006), particularly in car-dependent areas and among public transport captives. Parks (2004) also showed positive impacts of improved car job accessibility among some groups of low-skilled women. Three other studies found positive associations between combined measures of public transport and car job accessibility and (female) employment probabilities in the metropolitan areas of Mexico City (Quintanar, 2012) and Accra (Chen et al., 2017), and with employment stability of mainly aborigines in New Taipei City, Taiwan (Lin et al., 2014). Smart and Klein (2015), however, found a negative effect for public transport job accessibility among low-income and low-educated individuals across the US. As a higher number of household cars did increase their employment probabilities, this effect may be due to high car dependency. Yet again, endogeneity was not controlled for.

Three studies in more car-dependent US metropolitan areas that controlled for endogeneity found mixed results: Blumenberg and Pierce (2014) sampled low-income households on housing assistance but only found a positive association between public transport job accessibility and job retention, not with employment probabilities. Thompson (2001) used an IV-approach but found non-significance for male labour force participation and even a small negative association for female labour force participation. Both studies did find a positive association for car access. Hu (2016) sampled long-term residents and did find positive effects of better car job accessibility among medium- to low income groups, though not for the lowest or higher income groups.

Three European studies sampled long-term residents, finding that poor public transport and car job accessibility increased long-term unemployment probabilities in the Paris metropolitan area (Korsu and Wenglenski, 2010). More jobs were reachable per minute by public transport increased employment probabilities of low-educated women (Matas et al., 2010) and (only) female employment probabilities and youth living with their parents (Di Paolo et al., 2014) in the Barcelona and Madrid metropolitan areas. Other studies used an IV-approach and also found that better public transport and car job accessibility increased employment probabilities in Great Britain (Bastiaanssen et al., 2020b) and in The Netherlands (Bastiaanssen et al., 2020a, Bastiaanssen et al., 2020c), particularly among carless households in urban areas and low income groups.

Longitudinal studies in France found better public transport and car accessibility to jobs associated with shorter unemployment durations in the Paris metropolitan area (Gobillon et al., 2011), and with increased unemployment-to-work transitions (Détang-Dessendre and Gaigné, 2009). However, Gobillon et al. (2007) found no such association amongst public housing tenants in the Paris region. Sanchis-Guarner (2013) sampled workers affected by road construction in Great Britain, but found no effect of changes in car job accessibility on their hours worked or wages. Two US studies used longitudinal data of (involuntarily) laid-off workers, as their residential location can be considered exogenous to their employment status, and did find better public transport job accessibility associated with shorter unemployment durations (Rogers, 1997, Andersson et al., 2018). Ten other US studies utilized longitudinal welfare data but found that better car or public transport job accessibility sometimes improved welfare-to-work transitions (Alam, 2009, Sandoval et al., 2011) and job retention (Thakuriah and Metaxatos, 2000). However other studies found no significant effect (Bania et al., 2003, Cervero and Tsai, 2003, Sanchez et al., 2004, Bania et al., 2008), or even showed a negative association (Cervero et al., 2002, Shen and Sanchez, 2005, Blumenberg and Pierce, 2017). But, job accessibility between baseline and follow-up surveys is often not registered, or calculated for one year only, making longer-term employment outcomes uncertain.

Three other cross-sectional studies in US metropolitan areas found positive associations between better public transport or car job accessibility and youth employment rates (Ellwood, 1986, Raphael, 1998), and average weeks worked in (only) poor areas (Sanchez, 1999). Two studies in more car-dependent US metropolitan areas found no significant association between (changes in) public transport job accessibility and employment rates (Hu, 2015), and between car job accessibility and workers per capita at Census-level (Gao et al., 2008), while Hu and Giuliano (2014) used an IV-approach and did find positive effects of public transport job accessibility on employment rates in poor neighbourhoods. Other European studies also found positive associations between better public transport or car job accessibility and unemployment durations in the Paris metropolitan region, (Duguet et al., 2009), and with increased employment rates in central municipalities and among low-educated workers in Sweden (Norman and Borjesson, 2012, Norman et al., 2017). However, these studies could not control for personal or household characteristics, which may result in aggregation biases.

### *3.5 Discussion of main findings from systematic review*

What is clear from this systematic review of these past studies is that individual or household car ownership generally increases employment probability outcomes and that this effect persists in studies that control for endogeneity. Whereas dependence on public transport generally lowers employment probabilities, the studies suggest that better access to public transport and particularly the opening of new public transport infrastructure and subsidies facilitate job search and, hence, increase employment probabilities.

The predominantly US studies that use commute time measures generally find that lower mean commute times increase employment probability outcomes, which persists in studies that control for endogeneity. However, since commute times tend to rise with income, suburban locations with higher employment rates may actually have higher mean commute times than inner-city locations with lower employment rates (see Taylor and Ong (1995). Commute measures are also flawed because they are based on mean travel patterns of employed workers rather than actual individual's commute times, and may overlook those who are unemployed due to a lack of job access. Exclusively studying young people residing with their parents is more plausibly exogenous as they would not have self-selected their residential location, but labour market participation is often highly stable across generations (Clark, 2014), suggesting that parental residential location decisions may be spatially stratifying youth by ability.

Studies that use public transport or car accessibility measures to jobs generally find a positive association with employment probability outcomes, in particular in more car-dependent metropolitan areas and among public transport captives, even when controlling for endogeneity. However, more consistent job accessibility measures and complete datasets between baseline and follow-up surveys are needed to establish robust relationships between the key variables. A larger sample of studies that adequately control for endogeneity is also required to establish more robust relationships.

A feature of our constituent studies is that they predominantly were exploring the Spatial Mismatch Hypothesis (Kain, 1968) and so are based in areas of deprivation of large cities. The linkage between accessibility and employment may well be less strong in other situations such as smaller cities where dislocation from employment areas is less pronounced (see Ihlanfeldt (1992), for discussion). Even in segregated markets, other factors influence employment; Ihlanfeldt and Sjoquist (1998) find only up to half of employment rate differentials can be explained by accessibility. Only a few studies further distinguish the type of work - Berechman and Paaswell (2001) find in occupations with a proliferation of low-skilled jobs, improvements in accessibility have little impact.

## 4. Findings from meta-analyses of transport and individual employment probabilities

This section presents the results of our random-effects meta-regressions for studies using car ownership measures in section 4.1 and for studies using commute time measures in section 4.2, followed by conclusions in section 4.3. To account for study variation in terms of transport indicators, samples, and strategies to control for endogeneity, we further present random-effects GLS meta-regressions with study-specific covariates for both meta-regressions.

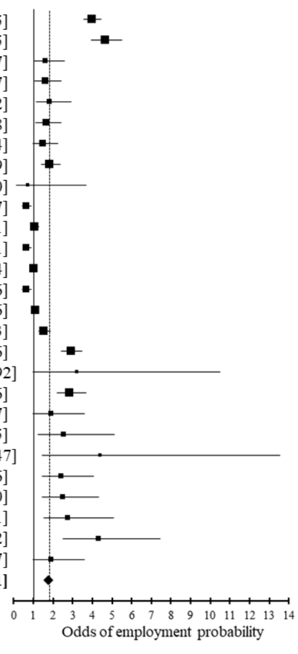
### *4.1 Car ownership and individual employment probabilities*

We identified 12 binomial logit model studies, providing 27 observations from the reported (sub)models that assessed the relationship between individual employment probabilities and individual or household car ownership (Table 1), with two studies by Bauder and Perle (1999) and Perle et al. (2002) using variables based on both one and multiple household cars[7]. Of these, 10 studies were conducted within the US context and two studies in Taiwan and the Czech Republic, often focussing on women, welfare recipients or young people (aged 16-25). All studies used cross-sectional employment models, of which three studies dealt with transport endogeneity between employment status and car ownership using an instrumental variable approach. Other studies dealt with residential endogeneity by using samples of youth residing at home or welfare recipients, as their residential location choice is considered exogenous.

As shown in Table 1, the studies mainly show odds-ratios larger than 1, indicating that car ownership increases individual employment probabilities. In particular, welfare recipients and low-skilled individuals seem to benefit from car ownership, but with strong variations in precision of their odds-ratios as indicated by their 95% confidence intervals. The lower odds-ratios (< 1) provided by the studies by Bauder and Perle (1999) for youth with access to single household cars as opposed to the higher odds ratios for access to multiple household cars may be due to the usage of multiple car measures. This increases the likelihood of multi-collinearity due to potential correlation between these measures, which may have biased the regression results.

Table 1. Meta-regression car ownership studies

| Study | Country | Sample | N | Measure | IV/S | Log Odds | SE | Weight | Odds ratio [95% CI] | Forest Plot Odds ratio [95% CI] |
|---|---|---|---|---|---|---|---|---|---|---|
| 1. Baum (2009) | US | W (F) | 8,158 | CAR (I) | S | 1.380*** | 0.057 | 4.57% | 3.975 [3.555, 4.445] | |
| 2. Baum (2009) | US | W (F) | 8,158 | CAR (I) | IV/S | 1.537*** | 0.087 | 4.49% | 4.651 [3.922, 5.515] | |
| 3. Baum (2009) | US | W (F) | 2,768 | CAR (I) | IV/S | 0.480** | 0.244 | 3.69% | 1.616 [1.002, 2.607] | |
| 4. Baum (2009) | US | W (F) | 2,766 | CAR (I) | IV/S | 0.467** | 0.212 | 3.88% | 1.595 [1.053, 2.417] | |
| 5. Ong (1996) | US | W (F) | 1,110 | CAR (I) | S | 0.607*** | 0.236 | 3.74% | 1.835 [1.156, 2.912] | |
| 6. Ong (2002) | US | W (F) | 770 | CAR (I) | S | 0.499*** | 0.194 | 3.99% | 1.647 [1.127, 2.408] | |
| 7. Ong (2002) | US | W (F) | 770 | CAR (I) | IV/S | 0.402** | 0.205 | 3.92% | 1.495 [1.000, 2.234] | |
| 8. Sullivan (2003) | US | LS | 934 | CAR (I) | | 0.610* | 0.133 | 4.31% | 1.840 [1.417, 2.389] | |
| 9. Sullivan (2003) | US | LS (F) | 459 | CAR (I) | | -0.320 | 0.830 | 1.17% | 0.726 [0.143, 3.690] | |
| 10. Bauder and Perle (1999) | US | Y | 13,048 | CAR1 (HH) | S | -0.4553*** | 0.177 | 4.08% | 0.634 [0.449, 0.897] | |
| 11. Bauder and Perle (1999) | US | Y | 13,048 | CAR2 (HH) | S | 0.0751*** | 0.029 | 4.62% | 1.078 [1.018, 1.141] | |
| 12. Bauder and Perle (1999) | US | Y (B) | 3,464 | CAR1 (HH) | S | -0.4361*** | 0.169 | 4.13% | 0.647 [0.464, 0.901] | |
| 13. Bauder and Perle (1999) | US | Y (B) | 3,464 | CAR2 (HH) | S | 0.0351*** | 0.014 | 4.63% | 1.036 [1.008, 1.064] | |
| 14. Bauder and Perle (1999) | US | Y (W) | 9,584 | CAR1 (HH) | S | -0.4575*** | 0.178 | 4.08% | 0.633 [0.477, 0.896] | |
| 15. Bauder and Perle (1999) | US | Y (W) | 9,584 | CAR2 (HH) | S | 0.1016*** | 0.039 | 4.60% | 1.107 [1.025, 1.196] | |
| 16. Perle et al. (2002) | US | Y | 13,385 | CAR1 (HH) | S | 0.4331**** | 0.094 | 4.47% | 1.542 [1.283, 1.853] | |
| 17. Perle et al. (2002) | US | Y | 13,385 | CAR2 (HH) | S | 1.0695**** | 0.091 | 4.47% | 2.914 [2.436, 3.486] | |
| 18. Lin et al. (2014) | TH | ABOR | 3,504 | CAR (I) | | 1.1753** | 0.600 | 1.82% | 3.239 [1.000, 10.492] | |
| 19. Shen and Sanchez (2005) | US | W | 9,815 | CAR (I) | S | 1.051*** | 0.128 | 4.33% | 2.861 [2.226, 3.676] | |
| 20. Yi (2006) | US | | 2,008 | CAR (HH) | | 0.640** | 0.327 | 3.18% | 1.896 [1.000, 3.597] | |
| 21. Blumenberg (2008) | US | W | 1,984 | CAR (HH) | S | 0.928*** | 0.360 | 2.97% | 2.529 [1.248, 5.125] | |
| 22. Blumenberg (2008) | US | W | 78 | CAR (HH) | S | 1.480*** | 0.575 | 1.91% | 4.393 [1.425, 13.547] | |
| 23. Blumenberg (2008) | US | W | 1,021 | CAR (HH) | S | 0.879**** | 0.267 | 3.54% | 2.408 [1.427, 4.066] | |
| 24. Blumenberg (2008) | US | W | 358 | CAR (HH) | S | 0.917**** | 0.279 | 3.47% | 2.502 [1.449, 4.320] | |
| 25. Blumenberg (2008) | US | W | 527 | CAR (HH) | S | 1.02**** | 0.310 | 3.28% | 2.773 [1.510, 5.091] | |
| 26. Marada and Květoň (2016) | CZ | | 1,023 | CAR (I) | | 1.466 | 0.277 | 3.48% | 4.332 [2.515, 7.462] | |
| 27. Hu (2016) | US | LINC | 1,284 | CAR (I) | IV/S | 0.64** | 0.327 | 3.18% | 1.896 [1.000, 3.597] | |
| **Overall Random Effect (I-squared 97.59%, p = 0.000)** | | | | | | **0.581*** ** | **0.104** | **100.00%** | **1.788 [1.460, 2.191]** | |




Heterogeneity: Tau2 = 0.232; Tau = 0.482; df = 26 (p < 0.00001)
Test for overall effect: Z = 5.608
Significance levels: *: 0.10% **: 0.05% ***: 0.01% ****: 0.001%

When we turn to the overall random effect of the meta-regression it shows a positive sign of 0.581*** with a related overall odds-ratio of 1.788, 95% CI [1.460, 2.191], p<0.001, which indicates that the odds of employment amongst individuals with access to a car are nearly 1.8 times higher than for carless individuals. Car ownership thus substantially helps people to gain employment.

[7] Abbreviations are reported in the appendix

To account for variation between the studies, we conducted a random-effects GLS meta-regression based on the log odds of the employment probabilities resulting from car ownership, with dummy variables for study specific covariates: i.e. ‘youth’ aged 16-25, ‘women’[8], ‘welfare recipients’, ‘multiple household cars’, and for ‘non-US studies’ (Table 2). A dummy based on studies that used instrumental variables to control for transport endogeneity was non-significant, as individual studies reported both increased and decreased log-odds ratios, so given the small number of observations in the model it was dropped. The coefficients in the model represent the estimated adjustments to the underlying log-odds ratio of car ownership from the various study level attributes The model is significant at 0.0001%, implying that these variables help to explain variations in individual employment probabilities.

Table 2. Meta-regression: Car ownership odds-ratios with study specific covariates

| Variables | Observations | Coefficient | Robust SE | P>\|z\| | Odds-ratio[9] |
|---|---|---|---|---|---|
| **Youth** | 8 | -0.644 | 0.352 | 0.068 | |
| **Women** | 8 | -0.513 | 0.201 | 0.011 | 0.940 |
| **Welfare recipients** | 13 | 0.623 | 0.155 | 0.000 | 2.428 |
| **Multiple hh cars (youth)** | 4 | 0.549 | 0.036 | 0.000 | 2.164 |
| **Non-US study** | 2 | 0.786 | 0.140 | 0.000 | 3.755 |
| **Constant** | | 0.534 | 0.072 | 0.000 | |
| **$R^2$** | 0.6362 | | | | |
| **Number of observations** | 27 | | | | |
| **Number of studies** | 12 | | | | |

The non-significant log-odds ratio adjustment for youth (aged 16-25) in Table 2 indicates that car access for youth has no differential impact on their employment over and above that of other (age) groups. Other factors than transport may mainly influence their employment prospects, such as lack of work experience or skills mismatches.

However, the highly significant and positive log-odds ratio adjustment for multiple household cars clearly shows that if access is to more than one household car, it does improve their employment probabilities, as indicated by the odds-ratio of 2.164. Young drivers may therefore benefit from access to household cars when these are not in use by their parents. The significant negative log-odds ratio adjustment for women indicates that their employment probabilities resulting from car ownership are lower than for studies that used pooled samples of men and women, as shown by their lower odds-ratio of 0.940. However, women with access to cars will still have better employment outcomes than those without cars, given most of these studies involve welfare recipients who clearly benefit from car ownership, as shown by the odds-ratio of 2.428. This is likely to follow from their low car ownership rates, relative to other population groups, while public transport may offer a poor substitute in car-dependent US metropolitan areas. Studies that were conducted outside the US-context clearly show a higher impact of car ownership on employment probabilities, however, a larger evidence base is needed to establish a more robust relationship between car ownership and employment outcomes.

### *4.2 Commute time and individual employment probabilities*

[8] The comparator for ‘youth’ is other (age) groups and for ‘women’ these are studies that used pooled samples of men and women.

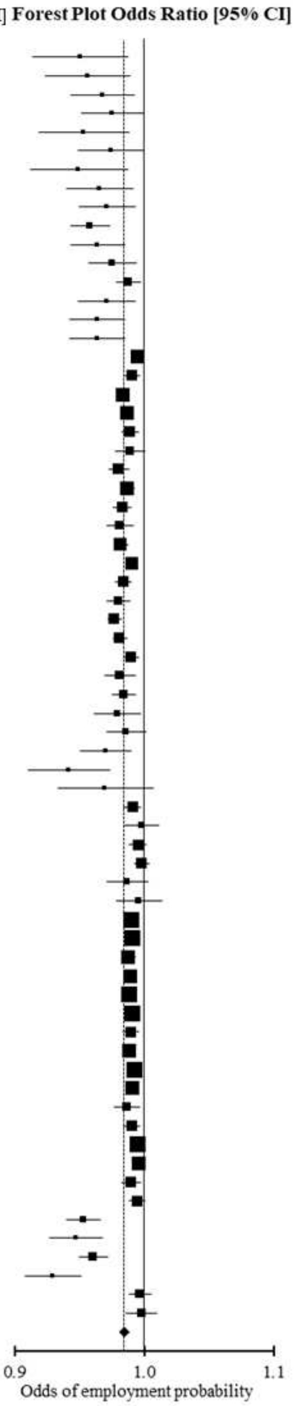
[9] The reported odds-ratios are derived from the sum of the log-odds ratio adjustment coefficient from the meta-model and the overall random effect log-odds ratio, exclusive of the study specific covariate subsample (e.g. excluding ‘youth’ based studies for the youth odds-ratio derivation).

We further identified 8 studies, providing 68 observations from the reported (sub)models that assessed the relationship between individual employment probabilities and mean neighbourhood commute times in minutes (Table 3). All studies were conducted within the US context, often focussing on employment differentials between Black, Hispanic, and white youth (aged 16-25). Mean commute times are typically based on one-way travel time to work derived from public microdata samples by residential zone, differentiated by socioeconomic or ethnic group. The studies used cross-sectional employment models, of which most studies reduced endogeneity by sampling young people living at home and one study sampling welfare recipients.

Overall, the studies in Table 3 show odds-ratios less than 1 with high precision as indicated by their small 95% confidence intervals, pointing towards a robust negative relationship between mean commute times and (decreasing) individual odds of employment. The overall random effect of the meta-regression shows a small negative sign of -0.014*** with a related odds-ratio of 0.986, 95% CI [0.985, 0.988], $p<0.001$, which indicates that as the mean commute times increase, the odds of employment slightly decreases; e.g. with a ten-minute increase in commute time we would expect the relative odds of employment to decrease by a factor of 0.14.

Table 3. Meta-regression commute time studies

| Study | Country | Sample | N | Measure | IV/S | Log Odds | SE | Weight | Odds ratio [95% CI] |
|---|---|---|---|---|---|---|---|---|---|
| 1. Holloway(1996) | US | Y (WE) | 32,164 | MCARCT | S | -0.051*** | 0.020 | 0.16% | 0.950 [0.914, 0.988] |
| 2. Holloway(1996) | US | Y (BNE) | 2,455 | MCARCT | S | -0.045*** | 0.017 | 0.20% | 0.956 [0.924, 0.989] |
| 3. Holloway(1996) | US | Y (BE) | 7,350 | MCARCT | S | -0.033*** | 0.013 | 0.36% | 0.968 [0.944, 0.992] |
| 4. Holloway(1996) | US | Y (WNE) | 5,795 | MCARCT | S | -0.025** | 0.013 | 0.36% | 0.975 [0.951, 1.000] |
| 5. Holloway(1996) | US | Y (WE) | 17,996 | MCARCT | S | -0.048*** | 0.019 | 0.18% | 0.953 [0.919, 0.989] |
| 6. Holloway(1996) | US | Y (WE) | 14,168 | MCARCT | S | -0.026** | 0.013 | 0.33% | 0.974 [0.949, 1.000] |
| 7. Holloway(1996) | US | Y (BNE) | 1,483 | MCARCT | S | -0.052*** | 0.020 | 0.15% | 0.949 [0.912, 0.988] |
| 8. Holloway(1996) | US | Y (BE) | 4,114 | MCARCT | S | -0.035*** | 0.014 | 0.32% | 0.966 [0.940, 0.992] |
| 9. Holloway(1996) | US | Y (BE) | 3,236 | MCARCT | S | -0.029*** | 0.011 | 0.44% | 0.971 [0.950, 0.993] |
| 10. Ihlanfeldt and Sjoquist (1991) | US | Y (BEH) | 5,694 | MCARCT | S | -0.0428*** | 0.008 | 0.77% | 0.958 [0.943, 0.973] |
| 11. Ihlanfeldt and Sjoquist (1991) | US | Y (WEH) | 8,394 | MCARCT | S | -0.0366*** | 0.011 | 0.46% | 0.964 [0.943, 0.985] |
| 12. Bauder and Perle (1999) | US | Y (NEH) | 13,048 | MCT | S | -0.0250*** | 0.010 | 0.57% | 0.975 [0.957, 0.994] |
| 13. Bauder and Perle (1999) | US | Y (BNEH) | 3,464 | MCT | S | -0.0124*** | 0.005 | 1.46% | 0.988 [0.978, 0.997] |
| 14. Bauder and Perle (1999) | US | Y (WNEH) | 9,584 | MCT | S | -0.0295*** | 0.011 | 0.43% | 0.971 [0.949, 0.993] |
| 15. Perle et al. (2002) | US | Y (EH) | 13,385 | MCT | S | -0.0371**** | 0.011 | 0.44% | 0.964 [0.943, 0.985] |
| 16. Perle et al. (2002) | US | Y (EH) | 13,385 | MCT | S | -0.0372**** | 0.011 | 0.44% | 0.963 [0.942, 0.985] |
| 17. Perle et al. (2002) | US | Y (EH) | 13,385 | MCT | S | -0.0049*** | 0.002 | 2.57% | 0.995 [0.991, 0.999] |
| 18. Perle et al. (2002) | US | Y (EH) | 13,385 | MCT | S | -0.0095**** | 0.003 | 2.17% | 0.991 [0.985, 0.996] |
| 19. Ihlanfeldt and Sjoquist (1990) | US | Y (WE) | 10,418 | MCARCT | S | -0.017 | 0.002 | 2.47% | 0.983 [0.979, 0.987] |
| 20. Ihlanfeldt and Sjoquist (1990) | US | Y (WE) | 10,418 | MCARCT | S | -0.013 | 0.002 | 2.58% | 0.987 [0.983, 0.991] |
| 21. Ihlanfeldt and Sjoquist (1990) | US | Y (BE) | 2,800 | MCARCT | S | -0.011 | 0.003 | 1.93% | 0.989 [0.982, 0.996] |
| 22. Ihlanfeldt and Sjoquist (1990) | US | Y (BE) | 2,800 | MCARCT | S | -0.011 | 0.006 | 1.18% | 0.989 [0.978, 1.000] |
| 23. Ihlanfeldt and Sjoquist (1990) | US | Y (WNE) | 3,519 | MCARCT | S | -0.020 | 0.004 | 1.71% | 0.980 [0.972, 0.988] |
| 24. Ihlanfeldt and Sjoquist (1990) | US | Y (WNE) | 3,519 | MCARCT | S | -0.013 | 0.003 | 2.22% | 0.987 [0.982, 0.992] |
| 25. Ihlanfeldt and Sjoquist (1990) | US | Y (BNE) | 1,182 | MCARCT | S | -0.017 | 0.004 | 1.85% | 0.983 [0.976, 0.990] |
| 26. Ihlanfeldt and Sjoquist (1990) | US | Y (BNE) | 1,182 | MCARCT | S | -0.019 | 0.005 | 1.31% | 0.981 [0.971, 0.991] |
| 27. Ihlanfeldt and Sjoquist (1990) | US | Y (WH) | 6,615 | MCARCT | S | -0.018 | 0.003 | 2.25% | 0.982 [0.977, 0.987] |
| 28. Ihlanfeldt and Sjoquist (1990) | US | Y (WH) | 6,615 | MCARCT | S | -0.009 | 0.002 | 2.66% | 0.991 [0.988, 0.994] |
| 29. Ihlanfeldt and Sjoquist (1990) | US | Y (BH) | 2,253 | MCARCT | S | -0.016 | 0.003 | 2.03% | 0.984 [0.978, 0.990] |
| 30. Ihlanfeldt and Sjoquist (1990) | US | Y (BH) | 2,253 | MCARCT | S | -0.020 | 0.005 | 1.48% | 0.980 [0.971, 0.989] |
| 31. Ihlanfeldt and Sjoquist (1990) | US | Y (WNH) | 6,253 | MCARCT | S | -0.023 | 0.003 | 2.19% | 0.977 [0.972, 0.983] |
| 32. Ihlanfeldt and Sjoquist (1990) | US | Y (WNH) | 6,253 | MCARCT | S | -0.019 | 0.003 | 2.19% | 0.981 [0.976, 0.987] |
| 33. Ihlanfeldt and Sjoquist (1990) | US | Y (BNH) | 1,405 | MCARCT | S | -0.010 | 0.003 | 2.12% | 0.990 [0.984, 0.996] |
| 34. Ihlanfeldt and Sjoquist (1990) | US | Y (BNH) | 1,405 | MCARCT | S | -0.019 | 0.006 | 1.11% | 0.981 [0.969, 0.993] |
| 35. Ihlanfeldt and Sjoquist (1990) | US | Y (BE) | 862 | MCARCT | S | -0.016** | 0.005 | 1.45% | 0.984 [0.975, 0.994] |
| 36. Ihlanfeldt and Sjoquist (1990) | US | Y (BE) | 556 | MCARCT | S | -0.021** | 0.009 | 0.60% | 0.979 [0.961, 0.997] |
| 37. Ihlanfeldt and Sjoquist (1990) | US | Y (BNEH) | 835 | MCARCT | S | -0.014** | 0.008 | 0.77% | 0.986 [0.971, 1.002] |
| 38. Ihlanfeldt and Sjoquist (1990) | US | Y (BNENH) | 453 | MCARCT | S | -0.030** | 0.010 | 0.51% | 0.970 [0.951, 0.990] |
| 39. Ihlanfeldt and Sjoquist (1990) | US | Y (BNEH) | 484 | MCARCT | S | -0.060** | 0.017 | 0.21% | 0.942 [0.911, 0.974] |
| 40. Ihlanfeldt and Sjoquist (1990) | US | Y (BNENH) | 368 | MCARCT | S | -0.031 | 0.019 | 0.17% | 0.969 [0.933, 1.007] |
| 41. Ihlanfeldt and Sjoquist (1990) | US | Y (WE) | 2,416 | MCARCT | S | -0.009** | 0.003 | 1.96% | 0.991 [0.984, 0.998] |
| 42. Ihlanfeldt and Sjoquist (1990) | US | Y (WE) | 2,034 | MCARCT | S | -0.002 | 0.007 | 0.99% | 0.998 [0.985, 1.011] |
| 43. Ihlanfeldt and Sjoquist (1990) | US | Y (WNEH) | 2,131 | MCARCT | S | -0.005 | 0.003 | 1.92% | 0.995 [0.988, 1.002] |
| 44. Ihlanfeldt and Sjoquist (1990) | US | Y (WNENH) | 1,882 | MCARCT | S | -0.002 | 0.003 | 2.18% | 0.998 [0.992, 1.004] |
| 45. Ihlanfeldt and Sjoquist (1990) | US | Y (WNEH) | 1,864 | MCARCT | S | -0.013 | 0.008 | 0.72% | 0.987 [0.971, 1.003] |
| 46. Ihlanfeldt and Sjoquist (1990) | US | Y (WNENH) | 2,319 | MCARCT | S | -0.004 | 0.009 | 0.65% | 0.996 [0.979, 1.014] |
| 47. Ihlanfeldt (1992) | US | Y (WH) | 24,342 | MCARCT | S | -0.0101** | 0.001 | 2.94% | 0.990 [0.989, 0.991] |
| 48. Ihlanfeldt (1992) | US | Y (BH) | 11,473 | MCARCT | S | -0.0091** | 0.001 | 2.87% | 0.991 [0.989, 0.993] |
| 49. Ihlanfeldt (1992) | US | Y (LH) | 4,962 | MCARCT | S | -0.0122** | 0.003 | 2.21% | 0.988 [0.983, 0.993] |
| 50. Ihlanfeldt (1992) | US | Y (LH) | 3,462 | MCARCT | S | -0.0109** | 0.002 | 2.60% | 0.989 [0.986, 0.993] |
| 51. Ihlanfeldt (1992) | US | Y (WENH) | 14,136 | MCARCT | S | -0.0120** | 0.001 | 2.90% | 0.988 [0.986, 0.990] |
| 52. Ihlanfeldt (1992) | US | Y (BENH) | 6,943 | MCARCT | S | -0.0089** | 0.001 | 2.85% | 0.991 [0.989, 0.993] |
| 53. Ihlanfeldt (1992) | US | Y (LENH) | 2,700 | MCARCT | S | -0.0106** | 0.003 | 2.08% | 0.989 [0.983, 0.996] |
| 54. Ihlanfeldt (1992) | US | Y (LENH) | 2,066 | MCARCT | S | -0.0120** | 0.002 | 2.47% | 0.988 [0.984, 0.992] |
| 55. Ihlanfeldt (1992) | US | Y (WNENH) | 10,205 | MCARCT | S | -0.0076** | 0.001 | 2.88% | 0.992 [0.991, 0.994] |
| 56. Ihlanfeldt (1992) | US | Y (BNENH) | 4,529 | MCARCT | S | -0.0094** | 0.002 | 2.62% | 0.991 [0.987, 0.994] |
| 57. Ihlanfeldt (1992) | US | Y (LNEH) | 2,261 | MCARCT | S | -0.01326** | 0.005 | 1.39% | 0.987 [0.977, 0.997] |
| 58. Ihlanfeldt (1992) | US | Y (LNEH) | 1,395 | MCARCT | S | -0.0099** | 0.003 | 2.03% | 0.990 [0.984, 0.996] |
| 59. Ihlanfeldt (1992) | US | Y (WNENH) | 6,477 | MCARCT | S | -0.0052** | 0.001 | 2.87% | 0.995 [0.993, 0.997] |
| 60. Ihlanfeldt (1992) | US | Y (BNENH) | 2,653 | MCARCT | S | -0.0046** | 0.002 | 2.50% | 0.995 [0.991, 0.999] |
| 61. Ihlanfeldt (1992) | US | Y (LNENH) | 2,338 | MCARCT | S | -0.0101** | 0.004 | 1.88% | 0.990 [0.983, 0.997] |
| 62. Ihlanfeldt (1992) | US | Y (LNENH) | 1,183 | MCARCT | S | -0.0057** | 0.003 | 2.06% | 0.994 [0.988, 1.001] |
| 63. Ihlanfeldt (1993) | US | Y (HEH) | 4,327 | MCARCT | S | -0.048** | 0.007 | 0.93% | 0.953 [0.940, 0.966] |
| 64. Ihlanfeldt (1993) | US | Y (HNEH) | 4,327 | MCARCT | S | -0.054** | 0.011 | 0.46% | 0.947 [0.927, 0.968] |
| 65. Ihlanfeldt (1993) | US | Y (WEH) | 4,506 | MCARCT | S | -0.040*** | 0.006 | 1.14% | 0.961 [0.950, 0.972] |
| 66. Ihlanfeldt (1993) | US | Y (WNEH) | 4,506 | MCARCT | S | -0.073*** | 0.012 | 0.40% | 0.930 [0.908, 0.952] |
| 67. Bania et al. (2008) | US | W | 605 | WMPTCT | S | –0.0031 | 0.004 | 1.59% | 0.997 [0.988, 1.006] |
| 68. Bania et al. (2008) | US | W | 634 | WMCARCT | S | –0.0022 | 0.006 | 1.09% | 0.998 [0.986, 1.010] |
| **Overall Random Effect (I-squared 79.98%, p = 0.000)** | | | | | | **-0.014*** ** | **0.001** | **100.00%** | **0.986 [0.985, 0.988]** |




Heterogeneity: Tau2 = 0.000; Tau = 0.005; df = 67 (p < 0.00001)
Test for overall effect: Z = -16.968
Significance levels: *: 0.10% **: 0.05% ***: 0.01% ****: 0.001%

To account for between study variation, we conducted a random-effects GLS meta-regression based on the log odds of the employment probabilities resulting from mean commute times, with dummy variables for study specific covariates: i.e. ‘youth’, ‘Black’ or ‘Hispanic’, and for studies that sampled youth ‘living at home’ to account for residential endogeneity (Table 4). The coefficients in the model represent the estimated adjustments to the underlying log-odds ratio of commute time from the various study level attributes. Since all studies were conducted within the US context and did not use an IV approach, we excluded these two dummies from the meta-regression. The model is significant at 0.0001%.

Table 4. Meta-regression: Commute time odds-ratios with study specific covariates

| Variables | Observations | Coefficient | Robust SE | P>\|z\| | Odds-ratio |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **Youth** | 66 | -0.021 | 0.006 | 0.000 | 0.976 |
| **Black youth** | 27 | -0.003 | 0.004 | 0.355 | |
| **Hispanic youth** | 10 | -0.002 | 0.002 | 0.354 | |
| **Youth living with parents** | 33 | -0.003 | 0.001 | 0.000 | 0.973 |
| **Car commute** | 60 | 0.004 | 0.005 | 0.446 | |
| **Constant** | | -0.001 | 0.003 | 0.781 | |
| | | | | | |
| **$R^2$** | 0.0489 | | | | |
| **Number of observations** | 71 | | | | |
| **Number of studies** | 8 | | | | |

Within the model, the significant negative adjustment to the log-odds ratio for commute times in the youth subgroup (aged 16-25) suggests more rapidly decreasing employment probabilities resulting from increased mean commute times as compared to other groups, as indicated by their lower odds-ratio of 0.976. With a ten-minute increase in commute time, the odds of employment amongst youth would decrease by a factor 0.24, which may imply that young people are more sensitive to the time and cost implications of longer commutes than other groups. In line with the seminal work of Kain (1968), all studies of young people assessed the differential employment impacts of longer mean commute times amongst Black and Hispanic youth, who typically live in poor inner-city neighbourhood, as compared to white youth, who tend to reside in suburban neighbourhoods. However, coefficients on being Hispanic or Black youth both show non-significance, which stresses that a given commute time for those being young and part of an ethnic minority does not have differential impacts on their employment probabilities over and above other groups. The variable 'youth living with parents' shows a significant but small negative log-odds ratio adjustment, indicating that the employment prospects of this group are slightly more sensitive to mean commute times than for other groups, as shown by the odds-ratio of 0.973.

Further, car commute shows a non-significant sign, from which we may infer that the different mode-based commute time measures used in the individual studies do not explain differences in employment prospects. Since the studies did not adequately address transport endogeneity (i.e. using an IV approach) the results must be carefully interpreted.

### *4.3 Discussion of findings from the meta-analysis*

In summary, the meta-regression models clearly demonstrate that car ownership significantly increases individual employment probabilities, in particular among groups with low levels of car access, such as welfare recipients. While car access for youth has no differential impact on employment over and above that of other (age) groups, access to multiple household cars does. The meta-regressions further showed that longer mean commute times are related to decreased individual employment probabilities. While young people in particular are more sensitive to the time and cost implications of longer commutes, our meta-regression models found no statistically significant variation between ethnic minority and white youth, as suggested in the literatures. The various job accessibility measures used in studies were found incompatible with each other and thus were unsuitable for a meta-regression.

While most studies were conducted in US metropolitan areas, evidence based on a limited number of studies suggests that similar patterns do hold in non-US metropolitan areas, but a larger evidence base is needed to establish a more robust relationship. It remains unclear, however, whether the same patterns would hold in smaller cities and towns outside the US-context where travel times and distances are shorter and/or where there has been less peripheral urbanization and decentralization.

Furthermore, endogeneity could be a possible problem with the featured studies given they are all based on cross-sectional models, which are interpreted as estimating long run relationships involving potential land use change. Few studies adequately controlled for endogeneity; although longitudinal studies can help to tease out endogeneity these were necessarily excluded because the interpretation of coefficients from these models is incompatible with those used in our meta-regression models.

## 5. Concluding remarks: public policy implications

By systematically merging 93 empirical studies of the relationship between transport access and employment probability outcomes in different geographical context and synthesising the data through meta-analysis, this study establishes a positive association between transport access and employment probability outcomes. It identifies varying effects for four identified categories of transport measures (or combinations thereof): car ownership, public transport access, commute times, and job accessibility levels. While most studies have focused only on metropolitan areas, often within the US context, evidence based on a limited number of studies in the systematic review suggests that similar patterns *do hold* in less car-dependent European metropolitan environments. This association persists in studies that have controlled for endogeneity by using, for example, an instrumental variable approach (see e.g. (Raphael and Rice, 2002, Bastiaanssen et al., 2020a). Longitudinal datasets have also been used to tease out endogeneity (see e.g. (Gurley and Bruce, 2005, Blumenberg, 2008), thereby overcoming the difficulties of finding appropriate instruments, but many studies lack complete datasets between baseline and follow-up surveys to fully establish an exogenous relationship. A larger evidence base is further needed to establish a more robust relationship between transport access and employment outcomes, in particular for smaller cities and towns outside the US-context and with regard to public transport.

Based on 20 methodologically comparable studies included in our meta-analysis, our meta-regression models clearly demonstrate that car ownership significantly increases individual employment probabilities, in particular among welfare recipients. While car access for young people has no differential impact on their employment over and above that of other (age) groups, residing in multiple car household does. The meta-regressions also show that longer mean commute times are related to decreased employment prospects, with young people in particular being more sensitive to the time and cost implications of longer commutes. However, there is apparent contradiction with the Spatial Mismatch literature (Kain, 1968), because young ethnic minority populations as compared with young people do not demonstrate differential employment effects with respect to a given commute time. Our systematic review further suggests that higher levels of public transport and car accessibility to jobs increases employment probabilities, but more consistent job accessibility measures are needed to establish a robust relationship through meta-regression.

Since the employment outcomes of job seekers could hypothetically thus be improved by better access to transport resources overall, it is suggested from our study results that *targeted policy interventions* would be needed to achieve this outcome. This is particularly important for people without access to private vehicles, such as low-income households, younger and older non-drivers and in areas under-served by public transport, such as rural areas and peripheral and deprived urban areas (Cervero et al., 2002, Blumenberg and Pierce, 2014). Most notably non-car owners often cannot afford to personally improve their transport alternatives by purchasing cars, but small-scale vehicle donation initiatives in the US (e.g. (Lucas, 2003)) and ‘Wheels to Work’ programs in the UK (Lucas et al., 2009) have been demonstrated to help people gain employment. This also implies that job seekers may benefit from public transport strategies targeted at improving their access to jobs.

On the other hand, bringing new employment opportunities closer to unemployed people might also help over the longer term, but this is notoriously difficult to achieve, as many failed regeneration initiatives over the years have demonstrated. Increasing private or public transport supply also does not necessarily mean a direct and associated increase in employment probability outcomes. There are many other factors to consider outside of transport supply such as education and skills and type of employment opportunities that are largely absent from aggregate models. What is clearer from our analysis, however, is that certain categories of individuals who are without private transport and who also currently have poor levels of access to public transport will have their employment opportunities significantly constrained.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## Appendix

We use the following abbreviations:

| | | |
|---|---|---|
| **Sample:** | W(F) | Welfare recipient (Female) |
| | LS | Low-skilled individuals |
| | M/F | Male or Female |
| | Y (B/L/W/CIT/SUB) | Youth (Black/ Latin (Hispanic)/ White/ Central city/ Suburbs) |
| | (E/NE/H/NH) | (Not) Enrolled in education/ (Not) Living at home |
| | (L/M)INC | Income class (Low- or Middle) |
| | ABOR | Aboriginals |
| **Transport:** | CAR (I/ HH) | Car ownership (Individual or Household) |
| | CAR1/2 (HH) | One or Multiple cars (Household) |
| | MCARCT | Mean car commute time |
| | M(G)CT | Mean (gravity-based) commute time |
| | WMCARCT | Weighted mean car commute time |
| **IV/S:** | IV | Instrumental variable approach |
| | S | Sample approach |

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