Final report

Bus fare and journey time elasticities and diversion factors for all modes

A rapid evidence assessment

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Preface

This report has been produced for the UK Department for Transport. It provides evidence on bus fare and journey time elasticities and diversion factors for all modes. The study uses a rapid-evidence review process, starting with systematic identification of relevant academic and grey literature through structured database searches as well as making enquiries to experts in the field in our networks to identify material, such as unpublished studies. This report summarises the key findings from analysis of the resulting evidence, as well as providing recommendations on values to be used in demand forecasting, appraisal and policymaking and identifying evidence gaps. While the primary audience for the document is the UK Department for Transport, it may be of wider interest for transport researchers and transport planners who wish to understand better the bus elasticities and diversion factors.

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Abstract

This study uses a rapid-evidence review process to identify evidence on bus fare and journey time elasticities and diversion factors for all modes (diversion factors quantify the impact of changes on one mode on the demand for other modes and for new trips). It uses a systematic search procedure to identify relevant academic and grey literature through structured database searches, as well as making enquiries to experts in the field to identify material, such as unpublished studies. The study focuses on material produced in or that is relevant to the UK. Little recent evidence on bus fare elasticities (in the UK) – and little evidence on bus journey time elasticities generally – was identified in the systematic search process. However, a substantial database of diversion-factor evidence was identified and collated. Recommendations are provided, based on analysis of the available evidence. In general, we find that the evidence on diversion factors is very diverse, covering a wide range of mainly metropolitan geographies, trip purposes, journey types and alternative transport options.

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Summary

RAND Europe and SYSTRA were commissioned by the UK Department for Transport (DfT) to undertake a review of the current evidence on bus-fare and journey-time elasticities and diversion factors.

Bus demand elasticities indicate the sensitivity of bus patronage to changes in relevant variables, such as price and journey time. They are fundamental to demand forecasting, investment decision and policymaking, and have been researched in the bus market since the 1970s.

Diversion factors are important in quantifying the impact of changes on one mode on the demand for other modes and for new trips. In transport appraisal they are used to determine the source and extent of new traffic resulting from an investment. In this case, diversion factors represent the proportion of new traffic on a mode that would otherwise have used another mode or that would not have travelled (called 'generated demand ').[1]

Values currently used for bus fare elasticities, generalised journey time (GJT) elasticities and diversion factors are mainly derived from the 'White Book' (TRL, 2004), which summarises the evidence available at that time.[2]

A revised set of elasticities and diversion factors are presented in this report. These are based on a detailed analysis of data from a wider set of studies, and include more recent evidence. For bus-fare and journey-time elasticities, the revised values do not differ from current guidance, although additional information is provided. For diversion factors, there are some substantial changes with values for additional modes and area-types included.

Diversion factors have been derived from a substantial, but diverse, database

Changes on a transport mode may result in demand being diverted to that mode from other modes, or from that mode to other modes. In this study we introduce the following definitions to make clear how the diversion factors should be used:

- **Intervention mode**. An intervention occurs **only** on this mode, resulting in a change in demand. Examples of interventions include: a new investment, a service improvement/deterioration or a policy change such as a congestion charge.

[1] It is also possible that there is a decrease in demand on a mode due, for example, to a deterioration in bus service. In that case, the diversion factor represents the proportion of demand diverted away from bus to other modes, or that no longer travels.

[2] Updated diversion factors to car from rail as intervention mode were published in July 2017. See DfT (2015).

- **Recipient/source modes**. These are all the modes that are affected by the change in demand on the intervention mode. Demand moves **from** these modes if there is a positive change in demand on the intervention mode. Demand may move **to** these modes if there is a negative change in demand on the intervention mode.

For a given intervention, the intervention mode and the recipient/source modes together make up the **choice set**, which consists of all the possible travel alternatives available to the traveller. Diversion factors **only** sum to one if they take account of the redistribution of demand across all possible alternatives, including not travelling or newly generated traffic.

Table A1 sets out recommended diversion factors for bus as the intervention mode for a number of area types and choice sets. Corresponding tables for interventions on other modes can be found in Chapter 4. Chapter 4 presents best-estimate values for a number of scenarios that are considered to be useful for transport appraisal purposes. It is intended for use without reference to the rest of the report and also provides an overview of the data and methodology.

Table A1: Recommended diversion factor values for an intervention on bus

Recipient/source mode	National weighted mean	Metropolitan[1]	Metropolitan (no light rail)	Metropolitan commute	Urban-conurbation[2]
car	0.24	0.25	0.30	0.30	0.30
rail	0.11	0.11	0.14	0.07	0.10
light rail	0.16	0.18		0.25	
cycle	0.04	0.06	0.07	0.07	0.04
walk	0.14	0.18	0.22	0.14	0.26
taxi	0.12	0.10	0.12	0.07	0.13
no travel	0.19	0.12	0.15	0.10	0.17
N[3]		94	86	19	25

Source: New analysis. Notes: 1. Data for metropoles (e.g. London) are combined with metropolitan. 2. There are no light rail data for urban conurbations. 3. N denotes the number of data points used to calculate the average.

It is important to note that the above central estimates are normalised averages over a range of data and should not imply precision not present in the data, given the number of dimensions, such as trip purpose, area type and study design, across which data have been reported. In Table A2 we present recommended ranges of diversion factors for interventions on bus, car, rail, light rail/metro, cycle and walk. These reflect the uncertainty in the data (approximately the 95% confidence intervals).

It is emphasised that the values currently used, which are based on the White Book, are derived from a small number of studies. They mainly fall within the recommended ranges or the differences can be explained by the data sources and choice sets used.

Table A2: Recommended diversion factors <u>for interventions on</u> bus, car, rail, light rail/metro and cycle

Intervention mode	Recipient/source mode						
	Bus	Car	Rail	Light rail / metro	Cycle	Walk	Generated traffic (no travel)
Bus		All trip purposes: 0.20-0.35 Commute: 0.30-0.55	Urban areas: 0.05-0.2 Intercity: 0.45-0.65	Urban areas: 0.05-0.35	Urban areas: 0.04-0.08	Urban areas: 0.1-0.3	Urban areas: 0.10-0.20 Interurban: 0.07-0.11
Car	Urban areas: 0.20-0.40 Interurban: 0.07-0.11		Urban areas: 0.05-0.20 Interurban: 0.55-0.75	Urban areas: 0.10-0.35	Urban areas: <0.1	Urban areas: 0.05-0.15	Urban areas: 0.1-0.25 Interurban: 0.10 - 0.25
Rail	Urban areas: 0.25-0.4 Interurban: 0.1-0.2	Urban areas: 0.3-0.45 Interurban: 0.4-0.55		Urban areas: 0.05-0.15	Urban areas: <0.1	Urban areas: <0.05	Urban areas: 0.10-0.20 Interurban: 0.10-0.20
Light rail / metro	Urban areas: 0.25-0.4	Urban areas: 0.15-0.3	Urban areas: 0.15-0.3		Urban areas: < 0.1	Urban areas: < 0.05	Urban areas: 0.10-0.20
Cycle	0.150.05-0.4, higher for walk and bus						

The evidence on diversion factors assembled from the literature review, although considerable, is also diverse. In the studies reviewed, data have been collected on diversion rates across a large number of modes and choice sets of alternatives, which depend on circumstances and interest. For example, relevant alternatives in urban conditions may include walk, cycling and light-rail, which would not normally be considered in interurban studies. Data have also been obtained using different research methods (discussed in the following section).

In addition to diversion factors being distinguished by area or journey type, in some studies they are segmented by trip purpose or by user type.

In total 934 diversion factors were obtained from the literature for ten modes. It is noted that one paper could generate multiple diversion factors. While this is a sizeable amount of data, it is not very large when considering the aim of identifying diversion factors between pairs of modes, including from and to bus, rail, car, light rail/metro, walking and cycling, and taking account of geographical area and passenger type (full-paying and concessionary travellers).

The literature review includes studies from Europe, USA and Canada, Australia and New Zealand as well as the UK. Although most of the data is from the UK (803 of the 934 diversion factors), including data from other countries has been useful for modes where data is sparse. This is particularly the case for cycle where more than half of the data on diversion from this mode and a quarter of data on diversion to this mode comes from outside the UK.

Most diversion factor data are available from interventions on bus, rail and car. Over half of the data is for urban areas and about a third for intercity areas (in about a tenth of the studies the geographic coverage is not defined). In the urban areas, nearly 90% of the data is for metropolitan areas with 5% for urban-conurbations. There is little data for small towns or rural areas. Only 13 diversion-factor values were available for concessionary travellers.

More and better evidence on diversion factors should be collected

In order to be able to explore the wide range of diversion factors desired – by the mode from which traffic would come from, the mode it would be diverted to and by geographical area – a large evidence base is required. In particular, most studies included in the dataset cover metropolitan areas and more data are needed on diversion factors for journeys in urban-conurbations, small towns and rural areas. Moreover, to understand better the influence of other explanatory factors, such as the type of intervention or the impact of the research methodology, even more data are required. We also note that the set of travel alternatives on which the diversion is based also has an impact on the diversion factor. Again, this is difficult to isolate without more data. Moreover, diversion factors are not symmetric[3] and can only be determined for interventions on modes for which reported data are available. We have presented diversion factors for bus, car, rail, light rail and cycle but the data on cycle interventions is limited and there are no data on interventions aimed at pedestrians.

While we have restricted ourselves to studies based on observed data, we have included transfer price and transfer time, or stated best alternative from surveys to provide evidence on actual behaviour (modelling and stated preference studies were excluded). While in general we do not see substantial differences in the diversion factor values across these sources, it would be better to focus on estimates of observed estimates from real transport changes. Efforts should be made to collect such evidence when evaluating impacts from transport interventions. These data could be compiled, over time, to complement the work that has been done in this study.

Very little new evidence on bus fare elasticities has been uncovered in the review

Our literature search identified very little new British evidence on bus fare elasticities, with the most recent work in this area being undertaken in the Toner et al. (2010) study. It is interesting that the Toner et al. (2010) recommendations for short run (SR) fare elasticities for the full-fare market are very much in line with the equivalent Dargay & Hanly (1999) recommendations, thereby supporting official guidance. The major review study of Wardman (2014) also finds the bus fare elasticities to be in line with these two

[3] It is important to distinguish between symmetry and equivalence. Diversion factors are not symmetric. The diversion factor for rail due to an intervention on bus is not equal to the diversion factor for bus due to an intervention on rail. See Section 3.1 for more details.

studies and official guidance. Hence we do not recommend any changes to the overall range of values for bus fare elasticities. However, based on the additional evidence from Wardman (2014), additional recommended values for area type and trip-purpose segmentations are included in Table A3.

Table A3: Recommended values for bus fare elasticities

Overall[1]	LR	-0.7 to -0.9	
Segmentation		Urban	London and rural
Commute	SR	-0.30	-0.40
	LR	-0.65	-0.85
Leisure	SR	-0.40	-0.55
	LR	-0.85	-1.10

Notes: 1: 6.4.24 of WebTAG unit M2 (DfT 2017); LR = long-run, SR = short-run

While there is consistency in the empirical evidence concerning the fare elasticity in the full-fare market, which is of primary interest, again this evidence is dated and much has happened in the bus market and its broader environment more recently. It is therefore timely to revisit bus-travel demand fare elasticities. Future estimation work needs to focus on the full-fare market, also taking account of concessionary travel since a sufficiently long time series now exists for this group of users.

Further, previous studies have shown that the bus fare elasticity is not a single number. There should be appropriate consideration of elasticity variations according to the fare charged, local market conditions, area type and other factors that can be investigated that might impact on bus fare elasticities.

Further, we have uncovered very little new evidence on bus journey time elasticities

We find that there is very little evidence on bus in-vehicle time (IVT) or generalised journey time (GJT) elasticities partly because bus journey times are somewhat less variable than fares.[4] We are not aware of any studies that determine GJT elasticities directly. The GJT values presented in Table A4 are derived from IVT elasticity with further assumptions made regarding walk- and wait-time elasticities.

Table A4: Recommended GJT bus elasticities derived from IVT elasticities

	GJT bus elasticity
Overall	-1.1
Commute	-1.15
Leisure	-1.05

[4] GJT is a composite term covering in-vehicle time, walking time and waiting time. In principle, it could also include late arrival time, and distinguish – for example – boarding time and dwell time.

The two key pieces of work undertaken in the period of the review looking at bus journey time elasticities are TRL (2004) Demand for Public Transport update – evidence from which forms the basis of the Department's recommendations – and the review and meta-analysis of Wardman (2012), part-funded by the DfT, which is the most extensive such piece of work in the area.

The current recommendation is based on TRL (2004) and is derived from a small amount of evidence largely from the 1990s. It is not inconceivable that time elasticities in the bus market have changed since this period. There is also some uncertainty as to whether the reported elasticity is short-run, long-run or is essentially indeterminate. Nonetheless, the recommendation corresponds very closely with the bus IVT elasticity implied by the meta-model in Wardman (2012).

Both these sources of evidence point to an IVT elasticity of around -0.6. This seems credible, given that we would expect bus passengers to be less sensitive to time variations than to fare variations (–0.7 to –0.9). This IVT elasticity is used to derive the GJT elasticity of –1.1 presented in Table A4.

There is undoubtedly a dearth of up-to-date evidence in this area, with little or no distinction by key factors such as journey purpose or type of area. Should variations in bus IVT and more generally bus GJT be high on the policy agenda, then there is clearly a need for fresh primary research in this area.

A comprehensive approach was used to identify relevant evidence

In this study we used a rapid-evidence review methodology to collect and synthesise the evidence on bus elasticities and a range of diversion factors. In a rapid-evidence assessment a rigorous approach – similar to a systematic review – is used, but the scope is limited in terms of the date, language and sources of information searched. A two-pronged approach to identify relevant literature was used to ensure that a broad range of literature was included in the evidence review. Firstly we conducted a systematic search of academic databases for literature published in peer-reviewed journals, conference papers and work undertaken by universities and other institutions, including the DfT. This systematic search was complemented by contacting key individuals in academia, industry and other stakeholder agencies to identify additional relevant data sources.

The study team also had access to recent relevant material from a study on urban passenger mode shift and cross-modal demand effects funded by the Research Council of Norway (Fearnley et al. 2017), which incorporates a literature review and meta-analysis of international evidence on cross-elasticities and diversion factors. It also included recently completed reviews of bus fare elasticity evidence (SYSTRA, 2016a) and of time elasticity evidence (SYSTRA, 2016b) for Transport for Greater Manchester as part of their considerations of bus reforms. This review covered more recent evidence than TRL (2004), such as the major concessionary fare study undertaken by ITS Leeds, the Metropolitan Bus Model and evidence over the period 1968 to 2010 contained in the major meta-analysis of UK elasticity evidence by Wardman (2014).

Acknowledgements

We are grateful to the many experts we contacted for taking the time to respond to our queries regarding empirical evidence on bus fare and generalised journey time elasticities and diversion factors.

We are also grateful to our Quality Assurance reviewers, James Fox from RAND Europe and Jim Millington, for their useful comments and insights, and to John Parkin (UWE) for his input on diversion factor evidence relating to cycling.

Lastly, we are grateful for the valuable advice from the Department for Transport, who helped improve the quality of the final report.

Abbreviations

DfT	Department for Transport
GC	Generalised cost
GJT	Generalised Journey Time
GT	Generalised time
IVT	In-vehicle time
PDFH	Passenger Demand Forecasting Handbook (for rail)
PTE	Passenger Transport Executive
REA	Rapid evidence assessment

1. Introduction

In this study, RAND Europe and SYSTRA were commissioned by the UK Department for Transport (DfT) to undertake a review of the current evidence on bus-fare and journey-time elasticities and diversion factors. Bus demand elasticities indicate the sensitivity of bus patronage to changes in relevant variables, such as price and journey time. They are fundamental to demand forecasting, investment decision and policymaking, and have been researched in the bus market since the 1970s. Values currently used for bus fare and generalised journey time (GJT) elasticities in the UK are derived from the 'White Book' (TRL 2004), which summarises the evidence available at that time. However, this evidence is becoming dated, as the nature of the bus market has changed over recent years in terms of the franchising model and the introduction of concessionary fares.[5]

Diversion factors are important in quantifying the impact of changes on one mode on the demand for other modes and for new trips. In transport appraisal they are used to determine the source and extent of new traffic resulting from an investment. In this case, diversion factors represent the proportion of new traffic on a mode that would otherwise have used another mode or that would not have travelled (generated demand). However, it is also possible that there is a decrease in demand on a mode due, for example, to a deterioration in bus service. In that case, the diversion factor represents the proportion of demand diverted away from bus to other modes, or that no longer travels.

Diversion factors are also closely linked to cross-price elasticities that reflect the change in demand on one mode as a result of a price change on a second mode. Diversion factors allow these to be determined by looking only at the impact on demand across modes of an effective price change on one mode, irrespective of the size of the price change. They are defined between mode pairs and represent the proportion of the change in demand for one mode (where the price change occurs) that comes from a second mode.

The 'White Book' is also the source for diversion factors, mainly from and to bus and car and for generated demand for these modes. These values are based on data from a small number of studies published in the 1990s. While the White Book provides diversion factors from rail to bus and car in both urban and interurban settings, diversion factors for rail to/from other modes are currently taken from Department for Transport (DfT) Transport Appraisal Guidance Unit A5.4 (DfT 2015). These values have been generated by the National Transport Model. Further, other modes, including light rail, cycle and walk are becoming increasingly important for transport appraisal. However, for light rail there are

[5] The English National Concessionary Travel Scheme (ENCTS) entitling bus users of pensionable age to travel for free on local bus services was implemented in 2008.

currently no standard diversion factors and only limited values for cycle and walk, which are often combined in one slow mode.

The elasticities and diversion factors of interest for this study, and the current sources of these values, are shown in Table 1.

Table 1: Elasticities and diversion factors of interest

Technical values	Breakdowns	Current sources
Commercial market fare elasticities for buses	Overall, by area[6], by short-run/long-run, by distance travelled	TRL (2004)
GJT elasticities for buses	Overall, by short-run/ long-run	TRL (2004)
GJT elasticities for buses	By area, by distance travelled	New values of interest
Diversion factors for buses	Overall, by area, by passenger type (fare paying and concessionary)	TRL (2004)
Diversion factors for rail	Overall, by PDFH[7] flow categories	WebTAG Unit A5.4
Diversion factors for cars	Overall, by area	TRL (2004)
Diversion factors for metro/light rail	Overall, by area	New values of interest
Diversion factors for walking	Overall, by area	New values of interest
Diversion factors for cycling	Overall, by area	New values of interest

In this study we use a rapid-evidence review methodology to collect and synthesise the evidence on bus elasticities and a range of diversion factors. Based on the available evidence, we then identify a preferred set of values.

This report is organised as follows. In Chapter 2 we describe the literature review methodology. In Chapter 3, we analyse the evidence on diversion factors. Recommended diversion-factor values for use in transport applications are presented in Chapter 4. The current evidence on bus fare and generalised journey time elasticities is discussed in Chapter 5 and Chapter 6, respectively. Conclusions and recommended values from the evidence review are provided in Chapter 7.

[6] The area classifications for the UK are London (metropolis), metropolitan, urban conurbation, small towns and rural.

[7] Passenger Demand Forecasting Handbook (PDFH)

2. Literature review methodology

This chapter sets out the literature-review methodology used to gather evidence for the study.

2.1. Search methodology

A two-pronged approach was used to ensure that a broad range of relevant literature was identified for review and inclusion in the evidence review. Firstly we conducted a systematic search of academic databases for literature published in peer-reviewed journals, conference papers and work undertaken by universities and other institutions, including the DfT. While this search methodology also picked up grey literature (broadly defined as unpublished or non-peer-reviewed studies) – particularly reports published by large agencies – it was judged that much of the diversion-factor evidence would be reported in non-peer-reviewed and agency studies. Therefore, this systematic search was complemented by contacting key individuals in academia, industry and other stakeholder agencies to identify additional relevant data sources.

2.1.1. Systematic literature search

The methodology of a rapid evidence assessment (REA) was applied to the literature search. This type of review aims to be a comprehensive, systematic and critical assessment of the scope and quality of available published evidence. REAs follow a similar structure to systematic literature reviews, as outlined in the Government Social Research Network Guidance, in that they aim to be replicable and transparent, yet they have the advantage of being less resource-intensive. This is achieved by formally constraining the types of research to be reviewed, for example, in terms of location, language and publication date. In the context of this study an REA was appropriate as it allowed the literature search to focus on the UK, while capturing the most relevant data from other developed countries; a restriction on publication date also helped strike a balance between the need for evidence on trends and avoiding duplication of previous work.

A search protocol was developed to capture relevant evidence on the bus elasticities and diversion factors shown in Table 1 (see Appendix A for the detailed search protocol). The search protocol consists of search strategies and inclusion criteria. A number of separate, but not mutually exclusive, search strategies was implemented to cover the literature on all the technical values specified in the scope of work. The search strategies take account of the fact that elasticities and diversion factors may not be the main purpose of the papers searched and may not appear in the title, abstract or keywords. This approach tends to generate a large number of results but minimizes the risk of omitting relevant literature. The search terms were piloted on papers already known to the review team to test their efficacy and the final set of search terms was able to identify these papers. The main inclusion criteria were:

- English language studies from OECD/EU countries to minimise issues of transferability. Studies relating to large cities (metropolises) like London were included as a separate category, due to greater differences between their transport systems, and those of other locations.
- Studies published after 1990, with a focus on evidence from 2003 onwards that could not have been included in TRL (2004).
- Studies based on observed data to provide evidence from actual behaviour, stated best alternative from surveys or using transfer time or transfer price methodologies to directly estimate diversion-factor values. Values implied by mode choice models and stated preference studies were excluded.

Based partly on our experience from previous literature reviews, searches were implemented in the Transport Research International Documentation (TRID) database, Scopus and Web of Science.[8]

2.1.2. Use of existing databases and networks

Two further sources were used to supplement the systematic literature review.

Firstly, we reviewed work already undertaken to identify potentially relevant sources of data. This included the database that is being developed as part of a project on urban passenger mode shift and cross-modal demand effects funded by the Research Council of Norway (Fearnley, Flügel et al. 2017) and that incorporates a literature review and meta-analysis of international evidence on cross-elasticities and diversion factors. It also included recently completed reviews of bus fare elasticity evidence (SYSTRA, 2016a) and of time elasticity evidence (SYSTRA, 2016b) for Transport for Greater Manchester as part of their considerations of bus reforms. These reviews covered more recent evidence than TRL (2004), such as the major concessionary fare study undertaken by ITS Leeds, the Metropolitan Bus Model and evidence over the period 1968 to 2010 contained in the major meta-analyses of UK journey time and price elasticity evidence by Wardman (2012; 2014).

Secondly, we contacted approximately 100 researchers, practitioners and managers in academia and consultancy, industry bodies and other stakeholder organisations by email to identify additional resources and grey literature. While there was some duplication of the academic literature, this approach was designed to capture recent developments in the literature that may not yet have followed the peer review process, and technical values contained in high quality industry reports.

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[8] The TRID database integrates the content of two major databases: the Organisation for Economic Co-operation and Development's (OECD's) Joint Transport Research Centre's International Transport Research Documentation (ITRD) Database and the US Transportation Research Board's (TRB's) Transportation Research Information Services (TRIS) Database. Scopus is a large abstract and citation based database of peer-reviewed literature with over 53 million records in the fields of science, technology, medicine, social sciences, arts and humanities. Web of Science is a citation index, with more than 5,000 publications in 55 disciplines as well as 160,000 conference proceedings. Additional searches were also undertaken in EconLit.

2.1.3. Assembling the literature

The database searches resulted in a large number of citations due to the necessarily broad nature of the search strategies that were implemented. These were screened using titles and abstracts of studies identified from the literature search ('first pass'). The first screening phase was conducted within Endnote – specialist reference management software – and was based on the inclusion criteria from the search protocol outlined in Section 2.1.1 above. A similar approach was used to screen literature obtained from contacts. The resulting longlist was then screened a second time, in conjunction with senior project team members and DfT, to determine the list of final papers to be included in the review. The process of assembling literature to review for both search mechanisms is shown in Figure 1.

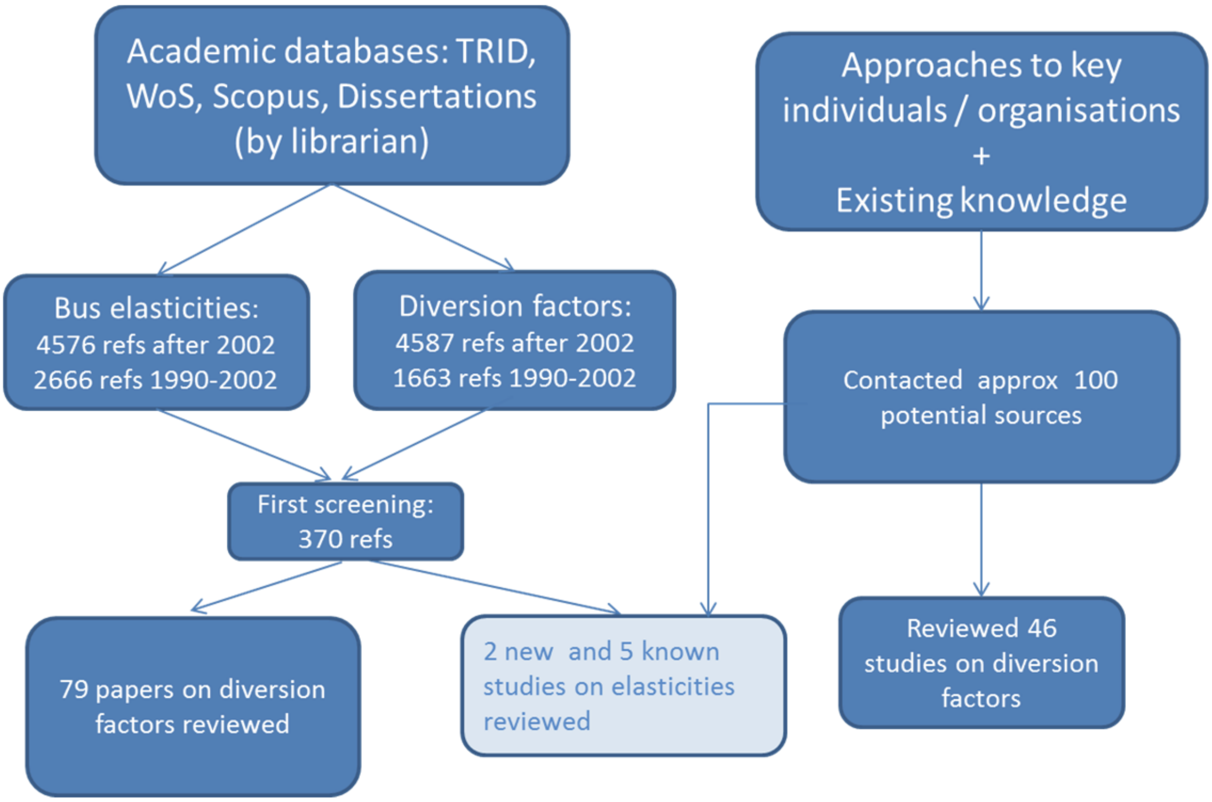

Figure 1: Summary of results from academic database searches and contacts

Only limited new evidence on bus fare elasticities or GJT elasticities, relevant to the UK, was identified from the literature searches (light blue box in Figure 1). However, a number of studies were already known to the project team. Chapters 4 and 5, respectively, discuss the bus fare and GJT elasticity evidence.

A considerable number of studies was identified that potentially contained evidence on diversion factors. These were supplemented by data from studies already known to the project team. Given the large number of papers to review and issues of transferability, studies outside of the UK, Europe, the USA and Australia, Canada or New Zealand were excluded at this stage. The remaining papers were reviewed in full, as described below.

2.2. Review of the literature and data extraction

The review and data extraction focused exclusively on diversion factors. An Excel spreadsheet was developed for the data-extraction phase. The information recorded from each study consisted of (where available):

- study identification information – number, authors, publication date
- publication type
- study location/country
- sample size, time period of data collection
- intervention (e.g. new infrastructure, service improvement/deterioration, policy/regulatory change)
- data type (e.g. observed data, best alternative, transfer time or transfer price)
- choice set of available travel options
- diversion factors by mode and by area segmentations
- other possible segmentations (trip purpose, journey type, passenger type)
- other segmentations of interest (income, gender, time of day)
- other comments.

Some of the above criteria relate to the quality and potential transferability of the diversion factors from other locations. Others provide contextual data that may help explain the variation in diversion factor values for mode pairs when determined for the specific segmentations of interest (overall and by area type). In total, data for 33 variables was recorded in the extraction spreadsheet. Many of these were coded as categorical variables to facilitate the analysis. Full details of the variables can be found in Appendix A.

Most studies provide only some of the above data, and some of the studies reviewed were found to contain no relevant diversion factors and were therefore excluded from the study at the extraction stage. Some attrition of this kind is inevitable because papers are shortlisted based on titles, keywords and abstracts only. This is particularly the case for diversion factors as they are often not the main focus of the study. Below we summarise the main features of the diversion-factor dataset that will form the basis of the analysis in Chapter 3.

Table 2: Main characteristics of diversion factor evidence dataset

Characteristic	Summary
No. of diversion factor values	1,009 from 45 studies.
Publication date	1982–2017, with over 60% of data in studies published in 2010 or later.
Publication type	20% of data from journals, 35% from published reports and 30% from unpublished reports.
Location of study	85% of data from UK.
Study design	Approx. 30% of data from observed change, 30% from reported best alternative, more than 35% from either transfer price or transfer time.
Intervention	45% of diversions were due to improvement or deterioration in service and 20% to new infrastructure.[1]
No. of modes	23 (including non-travel options)
No. of different choice sets (travel options)	50
Journey type	55% of data were for urban journey, 34% for interurban.
Area type	42% of data is for metropolitan areas, with only 2–3% for small towns and rural areas.[2]
Trip purpose	Data were collected for 14 trip purposes. 18% of data were from commute trips, 13% business travel and 28% from leisure trips.[3] For 30% of trips, no distinction by trip purpose was recorded.
Passenger type	Only 13 values were for concessionary travellers.
Other segmentations	There was little or no diversion factor data by income, gender, car availability or time of day (except commute).

[1] No intervention for reported best alternative; it assumes current mode no longer available. [2] Interurban journeys are not associated with an area type. [3] Here leisure trips include visiting friends and relatives and holidays or short breaks.

The dataset contains 1,009 diversion factors[9] obtained from 45 studies and covers a wide range of travel modes. However, it is very heterogeneous in terms of the characteristics of the underlying studies. In particular, the number of travel options that were recorded as available to users changing modes varied considerably across studies. These choice sets ranged from a simple choice between bus and car, to a larger set of alternatives such as bus, car, light rail, taxi, walk, cycle and not travelling. A more detailed discussion of the characteristics of the dataset and the number and values of diversion factors between different mode pairs is provided in Chapter 3.

[9] This is the number of diversion factors before any aggregation over modes.

3. Evidence on diversion factors

This chapter consists of three parts. We first provide a detailed introduction to diversion factors. Next we outline our approach to analysing the data and describe the dataset. We then discuss the detailed findings of the analysis. Recommended values, based on the analysis, are provided in a separate summary chapter (Chapter 4) and compared with the values currently available for use in appraisal.

3.1. Introduction

In this section we provide a definition of diversion factors, discuss their properties and then propose some terminology to make both their calculation and application unambiguous.

As noted in the introduction, in transport appraisal diversion factors are used to determine the source and extent of new traffic resulting from an investment. They can also help understand how a policy intervention on one mode can result in traffic moving away from that mode. Cross-price elasticities are defined between mode pairs and represent the percentage change in demand for one mode (*i*) that results from a 1% change in price on a second mode (*j*). Diversion factors allow these to be determined by looking only at the impact on demand on mode *i* of an intervention that causes an effective price change on mode *j*, irrespective of the size of the price change. Specifically:

$$\eta_{ij} \equiv \frac{p_j}{Q_i}\frac{\partial Q_i}{\partial p_j} = \frac{p_j}{Q_j}\frac{\partial Q_j}{\partial p_j}\frac{Q_j}{Q_i}\frac{\partial Q_i}{\partial Q_j} \tag{1}$$

where Q is demand and p price on a given mode. The term $\partial Q_i / \partial Q_j$ represents the proportion of the change in demand on one mode (*j*) that is diverted from another mode (*i*) when there is a price[10] change on mode *j* TRL (2004). However, $\partial Q_i / \partial Q_j \leq 0$ implying that an increase in demand on *j* will result in a decrease on mode *i*. Since diversion factors are reported as positive values, we define the diversion factor to be positive such that:[11]

$$D_{ij} = -\frac{\partial Q_i}{\partial Q_j} = -\frac{\partial Q_i}{\partial p_j} \Bigg/ \frac{\partial Q_j}{\partial p_j} \tag{2}$$

[10] By price change here, we mean a change in the generalised cost of using a mode that may arise from a fare increase, service frequency change or a new mode becoming available.

[11] We note that the diversion factor is denoted by $\partial Q_i / \partial Q_j$ in TRL (2004).

(see also Parry et al. (2007)[12]). This equation has a number of underlying implications:

1. $\sum_{i \neq j} D_{ij} \leq 1$. Diversion factors **only** sum to one if they take account of all possible changes in demand.[13] This is ensured by extending the definition of mode to include newly generated trips (or conversely trips no longer made)[14]; then diversion factors show how demand is redistributed across all other available modes when there is an effective price change on one mode. If the diversion factors do not sum to one, this is likely to be because data was not recorded for all possible travel choices. If, on the other hand, the diversion factors sum to one and the choice set does not include trips that were not previously made, then the intervention causing the diversion only results in redistribution of traffic across existing modes.
2. The choice set (i.e. the full set of available modes) has an impact on the magnitude of the diversion factor, both through the number and composition of modes.[15] Other factors, such as area type and car availability, may also play a role.

Choice set example (Box 1)
A new rail line is introduced. Travellers who use this route previously used bus or car or did not travel. 30% of new users come from bus, 40% from car and 30% did not previously travel. An improvement on an urban rail line draws users from bus (20%), car (55%), tram (10%), taxi (8%), walk (2%) and bicycle (5%).
The magnitude of the diversion factor from bus to rail is different in the two examples, where the choice sets are different (30% and 20% respectively). This is also the case for car to rail.

3. The diversion factor D_{ij} is the same regardless of whether the price change on mode *j* is positive or negative. If the price change is negative, then the diversion factor represents the proportion of additional traffic on mode *j* that comes **from** mode *i*. If the price change is positive, then the diversion factor represents the proportion of traffic leaving mode *j* that goes **to** mode *i*. This is the **equivalence**[16] property and is important both for how diversion factors are used and how they are calculated.

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[12] The notation is slightly different.

[13] $\sum_{i \neq j} D_{ij} = 1$ implies $\partial Q / \partial p_j = 0$ where $Q = Q_j + \sum_{i \neq j} Q_i$. We note that diversion factors can also be expressed as percentages, rather than proportions, as we have done in some examples. The diversion factors then sum to 100%.

[14] Indeed this can be extended to changing destination, time of day etc.

[15] Differentiating $\sum_{i \neq j} D_{ij} = 1$, we obtain $\frac{\partial Q_j}{\partial p_j} = -\sum_i \frac{\partial Q_i}{\partial p_j}$. Hence as the number and composition of modes changes, the diversion is affected via the denominator in equation (2).

[16] Equivalence is a form of symmetry but we prefer to use this terminology to avoid confusion with other forms of symmetry that are discussed later.

> **Equivalence example (Box 2)**
> A bus service has a certain level of demand (Q0). Suppose that an intervention (e.g. improved service frequency) occurs on the bus route that leads to increased demand for this service (Q=Q0+QN). 31% of this additional demand moving **to** bus (QN) is diverted **from** car, 6% from rail, 42% from walk/cycle and 21% is newly generated traffic.
> Now suppose that something else happens on the same bus route so that the demand for bus returns to its original level (Q0). This could be a reduction in service frequency but could also be another intervention such as a fare increase. Then 31% of the additional demand (QN) is diverted back **from** bus **to** car, 6% to rail, 42% to walk/cycle and 21% of these new bus trips are no longer made.
> In both cases 100% of the new bus traffic is accounted for in the diverted traffic.

We note that diversion factors defined above represent marginal effects; changes in demand due to relatively small price changes. In reality, non-marginal changes in circumstances – such as buying a car, investing in a season ticket or moving house – could have an impact on the diversion factors. However, equivalence is important as it allows different methodological approaches to be used to calculate diversion-factor values. We return to this issue in Section 3.2.2.

4. Diversion factors are **not symmetric**[17]. The diversion factor for bus to car is hardly ever likely to be the same as the diversion factor from car to bus. This is illustrated in the example below.

> **Symmetry example (Box 3)**
> There is an intervention on the roads that diverts traffic **to car** from other modes in the proportions: **0.48 from bus**, 0.24 from rail, 0.06 from walk/cycle and 0.22 from new trips. An intervention that diverts traffic **to bus** does so in the proportions: **0.31 from car**, 0.02 from rail, 0.42 from walk/cycle and 0.21 is newly generated demand.
> These two interventions affect the same choice set. However it is clear that when there is an effective price change for car, the proportion of new traffic diverted from bus to car (0.48) is not the same as the proportion of new traffic diverted from car to bus (0.31) when the intervention is on the bus mode.

5. Finally we note that the definition for the diversion factor, as expressed in equation (2), does not take into account the impact of segmentations – such as trip purpose, time of day, area type and journey length – on the shift in demand. Diversion factors may depend not only on the physical availability of a mode but also its accessibility and level of service for a given journey type. Equation (2) also says nothing about the method used to collect the empirical diversion-factor data or the intervention that gives rise to them. As noted earlier, diversion

[17] This stems from the fact that the base share of each mode may be quite different. Diversion factor symmetry would imply the same change in demand on both modes in response to a price change. This would not be the case, as can be seen from the standard specifications used to describe demand (e.g. constant elasticity), for which the price response would depend on the base share of demand.

factors represent marginal changes, whereas changes in behavior due to new infrastructure may occur over a longer time period (long-run).

The above discussion suggests that clear terminology is required to avoid both the potential misinterpretation of data collected by different methods to determine these values and the misuse of diversion factor values in transport applications. While diversion **to** and **from** modes or subscripts *i* and *j* are commonly used in the literature, as can be seen from the above examples on equivalence and symmetry, this may lead to some ambiguity.

We propose the following definitions:

- **Intervention mode**. An intervention occurs **only** on this mode that results in a change in demand. Examples of interventions include: a new investment, a service improvement/deterioration or a policy change such as a congestion charge.
- **Recipient/source modes**. These are all the modes that are affected by the change in demand on the intervention mode. Demand moves **from** these modes if there is a positive change in demand on the intervention mode. Demand may move **to** these modes if there is a negative change in demand on the intervention mode.

The intervention and recipient/source modes together form the choice set of modes available to the user. As well as physical modes, the choice set can include non-travel options or changing destination or route.

3.2. Methodology

A key aim of the study was to find evidence on diversion factors for bus, car, rail, light rail/metro, cycle and walk. Overall values for each of these modes and values by area type are desired. The evidence on diversion factors assembled from the literature review, although considerable, is also diverse. In the studies reviewed, data have been collected on diversion rates across a large number of modes, but these are also collected across a wide range of travel options (choice sets). The data are collected by different methods (study designs) and the intervention that gives rise to a diversion between modes varies between studies. Finally, in addition to diversion factors being distinguished by area or journey type, in some studies they are segmented by trip-purpose or by user type. These factors all raise methodological issues for the analysis.

3.2.1. Aggregation of modes

The dataset assembled in Chapter 2 consisted of 1,009 diversion-factor values covering diversion to and from mode pairs across 23 modes and 50 choice sets. Some aggregation was required to reduce the number of modes, and consequently, choice sets, to make the dataset tractable. The full dataset of 23 modes reported in the literature was therefore first aggregated to the minimum number of potential modes that encompassed the diversion factors of interest for the study. The aggregation is shown in Table 3. This aggregation resulted in some 'within mode' diversion. So, for example, diversion from high-speed rail to rail in the original data was recoded as a diversion from rail to rail in the aggregated data. This was dealt with by allocating the diversion across the other modes in the choice set on a pro-rata basis. So in the rail example, diversion from high-speed rail to rail was re-allocated to coach, car, air and no-travel.

Moreover, separate diversion factors from rail and high-speed rail to the other modes in the choice set were amalgamated. Hence the diversion factor from rail to car and high-speed rail to car, say, would be combined into one diversion factor from rail to car. The same process would then be applied to air and no-travel. Both the within-mode and between-mode aggregation therefore reduced the number of data points available for the analysis. The aggregated dataset consisted of 934 diversion factors covering diversion to and from mode pairs across 10 modes and 35 choice sets. It contains the same data as the original dataset but allocated across a reduced number of modes and choice sets.

Table 3: Aggregation of modes for diversion analysis

Mode (number)	Aggregated mode	Original mode(s)
1	Bus[1]	Bus, PT
2	car	car, car driver, car passenger, car share
3	rail	rail, HSR,
4	light rail/metro	light rail, metro
5	cycle	cycle, bike hire, walk/cycle[2]
6	walk	walk, walk/cycle
7	taxi	Taxi
8	air	Air
9	no travel	no travel
10	other	other mode, other bus, other station, change destination, change time of day, BRT

[1] Bus is synonymous with coach for interurban travel. [2] Allocated across separate walk and cycle modes.

3.2.2. Taking account of study design

Several research methods have been used in the literature to calculate diversion factors: observed changes in behaviour based on survey data, reported best alternative to main mode and stated intention collected in surveys and transfer time and transfer price. Diversion factors determined from models or stated preference methods were excluded. Cross-price elasticities are rarely validated in models, and, while based on user responses, stated preference studies usually elicit user responses to hypothetical future changes to an existing transport system. Moreover, the sensitivity of stated-preference experimental data is often questioned with regard to elasticities, and calibration to revealed preference data is recommended.

Most surveys reporting observed changes record the impact of an intervention on a particular mode, by asking users of that mode for the mode they previously used. An intervention in this case could be new infrastructure or an improvement to an existing service. These surveys thus report on actual behaviour in response to an intervention and record the shift from other modes and the new traffic generated by the intervention.

The remaining research methods are based on a second approach that involves asking transports users about potential changes in behaviour. Although not associated with a particular intervention, these methods determine the behaviour change that would occur when a mode is no longer available, or the journey cost or time make it unacceptable to a user. This could be for a number of reasons that are related to interventions, such as closure of infrastructure or reduction of services, fare increases or other policy measures.

The reported best-alternative method asks users of an existing mode what their best alternative would be if they could no longer travel by that mode. Hence, this method records the **potential** shift away from a given mode to other modes, which could include not travelling or changing destination.

The transfer price and transfer time methods operate on a similar principle. The study is designed to firstly determine the price or journey time at which a user would switch away from a given mode, and then what their subsequent travel behaviour would be.[18]

The dataset also contains a small number of stated intention responses for the closure of existing infrastructure; this is very similar to the reported best-alternative approach, asking users what they would do if their current mode became unavailable.

The diversion factors corresponding to different data-collection methods and interventions are summarised in Table 4.

Table 4: Study design and interventions

Intervention	Study design						
	Missing	Observed change	Reported best alternative	Stated intention	Transfer price	Transfer time	Total
Not relevant	0	3	294	0	0	0	297
New infrastructure	4	142	0	26	0	0	172
Improvement/ deterioration	0	76	0	0	224	139	439
Policy/regulatory change	0	14	0	0	0	0	14
Package of measures	0	12	0	0	0	0	12
Total	4	247	294	26	224	139	934

For each research method described above, there is one mode on which something occurs to change traveller behaviour. For the purposes of our analysis, this is denoted the **intervention mode**. For observed changes in behaviour, this is the mode users move to. For the research methods based on potential changes in behaviour, this is the mode users move from. In order to combine the diversion factors collected by the different methods in the analysis, we rely on the equivalence property discussed in Section 3.1. This essentially means that, all other things held equal, for observed changes the previous mode recorded is the same as the mode a respondent would choose if they could no longer use the new infrastructure or improved service. For example the proportion of users moving from rail to bus due to a

[18] For more information, see Lee & Dalvi (1969, 213–36).

railway station closure is the same as the proportion of bus users that would return to rail if the same station was reopened.

As shown in Table 4, about 26% of all diversion factors were determined from observed changes. In Section 3.3, where we discuss the findings of our analysis for different intervention modes, where possible we compare diversion factors calculated from observed behaviour data with those calculated from potential changes. However, this is only possible for mode pairs for which there are sufficient data. The total number of diversion factors between aggregated mode pairs is presented in Table 5.

Using the notation developed in Section 3.1, this table shows the modes on which an intervention occurs, after adjusting for the research method used. These do not cover all the possible (aggregated) modes simply because actual or potential interventions were not recorded for every mode. Interventions on some modes may be of more interest than others or the data may be easier to record. All modes are available as recipient/source modes in at least one study, however. As discussed in Section 3.1, diversion factors are not symmetric. So the diversion between bus as the intervention mode and walk as the recipient/source mode is not generally the same as the diversion between walk as the intervention mode and bus as the recipient/source mode. Mode pairs for which diversion factor values cannot be derived from the available evidence appear as zeros.

Table 5: Data available on diversion factors between mode pairs after aggregation and adjustment for data collection method

Intervention mode	Recipient/source mode									
	Bus	Car	Rail	Light rail/ Metro	Cycle	Walk	Taxi	Air	No travel	Other
Bus	0	63	33	8	13	13	10	9	44	37
Car	34	0	32	8	7	7	7	10	32	26
Rail	71	71	0	9	14	12	15	15	71	46
Light rail/metro	26	27	22	0	9	12	10	0	23	13
Cycle	8	7	4	5	0	7	1	0	1	3
Air	8	8	8	0	0	0	0	0	7	8
Total	147	176	99	30	43	51	43	34	178	133

These are the number of data points available to calculate overall values for diversion factors without taking account of variations across other dimensions.

3.2.3. Combining data from different sources

The aim of this study is to provide robust values for diversion factors between mode pairs that can be used for different area and journey types. We would therefore like to combine data across studies in some way. There are, however, a number of issues that need to be considered before undertaking the analysis.

Data on diversion factors has been assembled from 45 studies. Each study can be further disaggregated into sub-studies, which are differentiated by among other things intervention mode, choice set, time of day, distance and trip purpose. In total there are 220 sub-studies.[19] Each sub-study is unique as it

[19] We note that, if a study has no segmentation, it is considered to have one sub-study.

represents a particular study and segmentation combination. In the analysis we use segmentation to refer to the dimension along which data are grouped in a study. Hence, several studies could use the same segmentation by trip-purpose, for example.

Some studies in our dataset report data from more than one location, or are secondary sources. Others do not report the full choice set. However, taking into account segmentations within studies, in total almost 74% of diversion values sum to one.

Since diversion factor values do not sum to one for 30% of sub-studies, this means that the reported choice set may not reflect the full set of available alternatives or that data have not been collected or reported for all options due to the focus of the study on particular modes or the study design.

A further consideration is whether the choice set contains a no-travel (equivalently generated traffic) option. In our dataset 178 of the 220 sub-studies (81%) contain a no-travel option. For approximately 66% of these (146 sub-studies), the diversion factors sum to one. There are 33 sub-studies that report modal shift only.

Table 6: Summary data on sub-studies

	Number of sub-studies
No travel option	178
No travel option and diversion factors sum to one	146
Diversion factors sum to one	162
Total	220

For the ten aggregate modes, there are still 35 different choice sets underlying the diversion factor evidence. In some choice sets a mode may be the intervention, whereas for others it is the recipient/source mode. The number of choice sets involving each mode is summarised in Table 7. This shows, for example, that there are 25 different choice sets containing a no-travel alternative.

Table 7: Summary of choice sets that contain each mode

Mode (intervention and recipient/source)	Number of choice sets
Bus	31
Car	32
Rail	22
Light rail/metro	10
Cycle	14
Walk	15
Taxi	8
Air	2
No travel	25
Other	14

Although data were assembled from 45 studies, in fact over 50% of the values are taken from three sources: SYSTRA (2016a), Dargay (2010) and Vicario (1999). Data from Vicario (1999) were also used in the calculation of diversion factors presented in the White Book. However, these studies also contain a lot of segmentation (22, 62 and 14 segments respectively). Although the diversion factors for each segmentation do sum to one[20], this means that each diversion value is only calculated from a relatively small number of data points.

3.2.4. Variations across other dimensions

The diversion between mode pairs may also depend on the journey type.

The choice sets represent the travel options available and do not determine the journey type. So for example, bus, car, rail and no travel could be the available travel options for both urban and interurban journeys. However, some modes are only available for certain journey and area types as illustrated in Table 8.

Table 8: Number of diversion factors by recipient/source mode and journey type

Mode	Journey type			
	Urban	Interurban	No distinction	Total[1]
Bus[2]	73	58	16	147
Car	91	57	27	177
Rail	52	47	0	99
Light rail/metro	27	0	3	30
Cycle	41	0	2	43
Walk	48	0	3	51
Taxi	39	2	2	43
Air	0	34	0	34
No travel	78	76	20	182
Other	60	62	11	133
Total	509	336	84	934

[1] Includes additional missing values. [2] Bus is synonymous with coach for interurban travel.

In the urban area-type definition, we distinguish between a large metropolis, such as London, and other metropolitan areas, as well as urban conurbations and small towns.[21] Most of the data for urban journeys are concentrated in metropolitan areas. There is little data for rural areas.

[20] Values between 0.95 and 1.05 are assumed equal to one, given potential rounding errors during the aggregation.

[21] The area type classifications are based on the National Transport Model (NTM) and data provided directly by the DfT. For the purposes of this study, metropolis comprises inner and outer London, metropolitan area comprise other inner and outer conurbations, urban conurbations are urban areas with population great than 100,000 (equivalent to urban large and urban big categories from NTM) and small towns are urban areas with a population

Table 9: Number of diversion factors by recipient/source mode and area type

Mode	Area type					
	Large metropolis	Metropolitan	Urban conurbation	Small towns	Rural	No distinction
Bus	7	69	0	1	6	5
Car	7	79	13	4	9	5
Rail	2	49	1	0	0	0
Light rail/metro	3	24	0	0	0	3
Cycle	1	41	1	0	0	0
Walk	3	46	1	0	0	1
Taxi	0	40	1	0	0	0
Air	0	0	0	0	0	0
No travel	5	73	8	1	8	4
Other	4	50	6	1	7	3
Total	32	471	31	7	30	21

Note: Interurban journeys do not have an area type and are not included in this table.

In some studies, diversion factors have been determined for different trip purposes; in particular, commute, business and leisure travel. In total, 13 trip purposes are included in the dataset and no distinction is made for approximately one third of the data.

Table 10: Number of diversion factors by recipient/source mode and trip purpose

Mode	Trip purpose			
	Commute	Business	Leisure[1]	No distinction
Bus	25	20	43	40
Car	31	19	42	62
Rail	16	13	40	16
Light rail/metro	9	1	4	13
Cycle	7	3	3	20
Walk	11	4	3	25
Taxi	7	3	4	22
Air	0	8	21	4
No travel	28	24	58	47
Other	27	22	48	26
Total	161	117	266	275

[1] Leisure here included visiting friends and relatives and holidays/short breaks.

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between 25,000 and 100,000. A similar approach is applied to data from outside the UK. For example, a metropolis would be a city of a similar or larger scale to London.

The literature review included studies from Europe, USA, Canada, Australia and New Zealand, as well as the UK. Although most of the data is from the UK, including data from other countries may be useful for modes where data is sparse. This is particularly the case for cycle where more than 50% of data on diversion from this mode and 25% of data on diversion to this mode comes from outside the UK. Table 11 shows the number of data points by intervention mode for the different locations.

Table 11: Number of diversion factors by intervention mode and world region

Intervention mode	World region				
	UK	Northern Europe	Other Europe	USA	Canada/Australia /New Zealand
Bus	206	3	2	5	14
Car	158	2	0	3	0
Rail	255	9	8	6	46
Light rail/metro	132	4	4	2	0
Cycle	13	6	7	0	10
Air	39	0	0	0	0
Total	803	24	21	16	70

Data for other segmentations – such as time of day, gender or income – were not excluded from the study, but few or no data were recorded. Only 13 diversion-factor values were for concessionary travellers.

The data presented in this section and section 3.2.3 shows that diversion factor values have been obtained across a wide range of dimensions. In addition, as with all empirical data, there will be some unobservable variation associated with each diversion-factor set. Combining data across-choice-sets and segmentations also means that diversion factors cannot easily be constrained to sum to one. There is then a trade-off between using a wide range of data to reduce the variability in the calculated values and making sure that the total diverted demand does not exceed what is actually available. There is no *a priori* reason to weight diversion factors to meet this constraint, as this would imply an exactness not present in the data. We prefer to make the reader aware of the caveats involved in using the values presented in this study. However, normalising the final set of values for a given application would make sure all diverted demand is distributed across the available alternatives. This is discussed in Chapter 4.

While there may be sufficient data to analyse the impact of one dimension on diversion factors, the dataset is not large enough to control for effects across several dimensions and undertake meaningful regression analysis. A useful means of explaining variations in behavioural parameters such as diversion factors is some form of regression analysis. This commonly underpins meta-analysis of such things as values of time, fare elasticities and time elasticities. Thus we might regress diversion factors as the dependent variable upon factors that influence them, such as journey purpose, distance, data collection type and whether switching from a mode or the source of new demand.

We did not pursue this approach, with the time and resources available, because of a number of challenges. For example, the large number of choice sets – which has a direct bearing on the diversion factors – complicates matters, while any analysis would have to ensure that the relevant diversion factors summed to one. Our expectation was that any such model would have had to contain such a large range of variables to account for all possible circumstances as to make it a tool that would be difficult to interpret and use. We have therefore relied on cross-tabulations against key variables to explore the variations in the assembled diversion factors.

3.3. Findings

This section is organised as follows. We first discuss the variation between diversion factors across segmentations for the same choice set using the three largest studies in our dataset. We then discuss diversion factors for each **intervention** mode in turn for which data are available. These are bus, car, rail, light rail/metro, cycle and air. For each mode we further discuss the role of choice sets, which differ in the number and type of modes that are available to the user. For each intervention mode, we also provide average (mean) diversion factors for every recipient/source mode, across all of the data collected in the review exercise and derived from UK data only. We also present values for urban and interurban journeys, and, where available, for area type. Information on the number of observations ('N'), the number of studies and the standard error is also included.[22]

Appendix B provides more detailed tables, showing results by research methodology and other segmentation variables. It also includes diversion factors, separately by choice set for each mode, which we also draw upon in the following discussion.

In the following sections we will use the notation of intervention and recipient/source modes developed in Section 3.1. As noted there, diversion may occur to or from the intervention mode. However, for clarity, in the discussion we will refer to diversion 'from' the intervention mode only (and consequently 'to' the recipient/source mode).

3.3.1. The three key studies in the dataset

For the first part of the analysis we focus on the three studies referenced in Section 3.2.3.[23]

The study of diversion factors in Greater Manchester (SYSTRA, 2016a) provides diversion factors for interventions on the bus, car, rail and light rail/metro modes, where users can choose between these four modes as well as cycle, walk, taxi, not to travel and other. A number of segmentations by trip purpose,

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[22] The standard error is defined as the standard deviation/square root (N). 95% confidence intervals are calculated as 1.96 x standard error. While each diversion value in the dataset has been derived using an empirical sample, the associated standard errors are not often reported. We have calculated these based on the sample size. These are used for comparison between studies. For the main analysis we implicitly assume that all samples have approximately the same standard error. Confidence intervals for small samples, based on t-values, may differ from the 1.96 x standard error. The large sample approximation, which provides upper bounds for these intervals, is considered reasonable given the uncertainty in the data.

[23] Our analysis is based on aggregated modes and may therefore differ from the results presented in the original reports.

distance and car availability are considered. The diversion factors calculated across these segmentations are presented in Table 12.

The results show some differences in the diversion factors for commuters and those travelling on personal business. The most striking results are for distance travelled and car availability. An intervention on bus has a greater effect on rail and car users for short distances as well as for walk and cycle. Car availability has a strong impact on diversion factors between other modes. For example, if travelling by bus became less attractive, then 75% of bus users with a car available would travel by car instead and only 3% by light rail/metro. For bus users without a car available, 11% would choose light rail/metro and 18% would choose not to travel.

Most studies do not distinguish between diversion factors for travellers with and without car availability and it is assumed that the diversion factors represent the diversion over a population that is consistent with the proportions of travellers who have access to a car for their journey and those who do not. This is the case for the other diversion factors presented in Table 12, which are much smaller (e.g. 33% bus-car).

Vicario (1999) also reports diversion by trip purpose in an urban setting (Leeds) for interventions on bus, car and rail. These are reproduced in Table 13. For urban journeys this dataset has a similar choice set to the Greater Manchester study; it does not have a light rail/metro option but it does include not travelling. A slightly different set of trip-purposes are considered, with commute common to both. Table 13 shows that the diversion factor for bus commuters is higher than for other trip purposes, but the result is not so clear for car and rail interventions. Choosing not to travel is also a clear option for users of these two modes, particularly for leisure travel. The Greater Manchester and Leeds studies have different choice sets. While diversion to rail is generally higher for the Leeds study, which does not contain a light rail option, it is comparable to the combined diversion to rail and light rail in the Greater Manchester study. For commute, the diversion factors from bus to car and from rail to bus are generally found to be higher in Leeds (e.g. 0.45 compared with 0.33 for bus to car). This could possibly be explained by differences in the bus services between the two cities. The Vicario (1999) study also looks at interurban journeys for business and leisure purposes (Table 14).

The other main source of data on interurban journeys is Dargay (2010). That study considers journeys by distance as well as intervention mode and trip purpose. In Table 15 we present some of these results only, although all the data are used in the analysis in the following sections. The choice set in Dargay (2010) for journeys over 150km is the same as in Vicario (1999) and also covers the same intervention modes and trip-purposes, among a wider range of segmentations. Comparing the results we see that some values are quite consistent: diversion to car when there is an intervention on rail, diversion to bus for an intervention affecting car. However, there are quite large differences in values for the no-travel alternative when car is the intervention mode and for diversion to air from rail.

The findings of this section illustrate how diversion factors can differ between studies due to the study design and other factors – such as location and choice set – but can also show a good degree of consistency.

Table 12: Diversion factor for Greater Manchester (SYSTRA, 2016a)

Intervention mode	Segmentation	Bus	Car	Rail	Light rail/metro	Cycle	Walk	Taxi	No-travel	Other
Bus	Commute		0.33	0.10	0.05	0.08	0.15	0.13	0.09	0.08
Bus	Personal business		0.34	0.07	0.08	0.03	0.11	0.16	0.13	0.07
Bus	<10km		0.34	0.07	0.07	0.04	0.15	0.17	0.10	0.05
Bus	>10km		0.32	0.12	0.09	0.05	0.04	0.10	0.11	0.12
Bus	Car available		0.75	0.03	0.03	0.02	0.06	0.06	0.04	0.02
Bus	No car available			0.13	0.11	0.07	0.17	0.23	0.18	0.11
Bus	All		0.42	0.09	0.07	0.05	0.11	0.14	0.11	0.08
Car	Commute	0.23		0.06	0.06	0.13	0.10	0.11	0.17	0.14
Car	Personal business	0.21		0.07	0.08	0.03	0.13	0.17	0.20	0.10
Car	<10km	0.29	0.03	0.03	0.04	0.11	0.16	0.13	0.15	0.10
Car	>10km	0.15		0.11	0.12	0.06	0.03	0.15	0.24	0.14
Car	All	0.22		0.07	0.08	0.08	0.11	0.14	0.19	0.12
Rail	Commute	0.15	0.50		0.07	0.02	0.02	0.08	0.10	0.15
Rail	Personal business	0.20	0.47		0.12	0.01	0.01	0.06	0.10	0.20
Rail	<10km	0.23	0.46		0.09	0.03	0.01	0.05	0.09	0.23
Rail	>10km	0.15	0.50		0.11	0.01	0.01	0.07	0.10	0.15
Rail	Car available	0.05	0.84		0.05	0.01	0.00	0.02	0.01	0.05
Rail	No car	0.36			0.17	0.02	0.03	0.14	0.21	0.36
Rail	All	0.19	0.55		0.10	0.02	0.01	0.07	0.10	0.19
Light rail	Commute	0.23	0.40	0.07		0.05	0.02	0.11	0.08	0.04
Light rail	Personal business	0.27	0.36	0.10		0.02	0.02	0.11	0.08	0.03
Light rail	<10km	0.31	0.35	0.07		0.03	0.04	0.09	0.07	0.04
Light rail	>10km	0.21	0.41	0.10		0.04	0.00	0.12	0.09	0.02
Light rail	Car available	0.70	0.11	0.07		0.02	0.01	0.05	0.01	0.03
Light rail	No car	0.42		0.11		0.04	0.03	0.18	0.16	0.04
Light rail	All	0.36	0.33	0.09		0.03	0.02	0.11	0.08	0.03

Table 13: Diversion factors for urban journeys in Leeds (Vicario 1999)

Intervention mode	Segmentation	Bus	Car	Rail	Cycle	Walk	Taxi	No-travel	Other
Bus	business		0.32	0.12	0.07	0.41	0.03	0.03	0.04
Bus	commute		0.45	0.12	0.07	0.31	0.02	0.01	0.01
Bus	leisure		0.20	0.07	0.02	0.52	0.10	0.08	0.00
Car	business	0.49		0.28	0.01	0.05	0.00	0.10	0.06
Car	commute	0.51		0.28	0.01	0.08	0.01	0.06	0.08
Car	leisure	0.42		0.15	0.00	0.05	0.02	0.33	0.02
Rail	business	0.35	0.59		0.00	0.00	0.00	0.06	0.00
Rail	commute	0.52	0.41		0.00	0.00	0.00	0.05	0.03
Rail	leisure	0.53	0.35		0.00	0.00	0.00	0.12	0.01

Table 14: Diversion factors for interurban journeys (Vicario 1999)

Intervention mode	Segmentation	Bus	Car	Rail	Air	No-travel
Bus	leisure		0.22	0.59	0.02	0.18
Car	business	0.06		0.45	0.01	0.49
Car	leisure	0.13		0.39	0.01	0.47
Rail	business	0.35	0.59		0.20	0.04
Rail	leisure	0.28	0.53		0.06	0.13

Table 15: Diversion factors for interurban journeys (>150km) (Dargay 2010)

Intervention mode	Segmentation	Bus	Car	Rail	Air	No travel	Other
Bus	business		0.25	0.44	0.13	0.17	0.04
Bus	leisure		0.32	0.44	0.05	0.08	0.09
Bus	VFR		0.23	0.62	0.08	0.08	0.02
Bus	Holidays/short break		0.40	0.32	0.10	0.10	0.07
Car	business	0.02		0.77	0.14	0.06	0.02
Car	leisure	0.08		0.67	0.06	0.14	0.04
Car	VFR	0.08		0.72	0.07	0.13	0.01
Car	Holidays/short break	0.12		0.47	0.08	0.14	0.20
Rail	business	0.07	0.63		0.39	0.09	0.03
Rail	leisure	0.10	0.45		0.27	0.12	0.05
Rail	VFR	0.14	0.47		0.29	0.09	0.04
Rail	Holidays/short break	0.05	0.31		0.40	0.13	0.12

In the analysis we have not included the option 'must use current mode' and rescaled diversion factors to other modes to sum to one.

3.3.2. Diversion from bus as intervention mode

The analysis in this section is based on data from 17 studies, covering 16 choice sets for which bus is the intervention mode. The diversion factors by choice set are shown in Table 47, Appendix B. Standard errors are provided for diversion factors that are based on data from more than one study.

The diversion factors presented in Table 47 are not differentiated by trip-purpose, journey type or other segmentations. However, the choice sets for bus can be broadly divided into those that service urban journeys and those that cover interurban journeys (i.e. coach travel). For the urban case, the values calculated for diversion to cycle and rail are quite consistent between choice sets, but some studies report much greater diversion to car than others. This reflects the fact that diversion factors for commute and for car availability (SYSTRA, 2016a) are included. The standard errors indicate that there is also quite a lot of variation within the choice sets for the diversion values across all the recipient/source modes. The diversion factors for interurban travel are based on Vicario (1999) and Dargay (2010) when air travel is an alternative and on Dargay (2010) alone when the choice set does not contain air travel. The results show that there is greater diversion from bus to rail than to car and very little to air: in the UK, the length of journeys by air is such that coach is too slow to be competitive.

The data obtained from all choice sets are summarised in the average values presented in Table 16. These results indicate that the diversion to car is fairly stable across journey type. Diversion to rail is much higher for interurban journeys than for urban ones, even when the rail and light-rail share are combined.

Diversion factors by area type are also of interest for this study. Most data were for metropolitan areas. Although it is often difficult to determine the urban area type for a given study, diversion factors to car that were different from the urban average were found for small towns (0.42, s.e. 0.15, N=3) and rural areas (0.19, s.e. 0.08, N=3). Only a small number of data points were available – all from UK studies – for diversion from bus to car in rural areas, with no-travel the only alternative studied (0.38, s.e. 0.13, N=2). The evidence dataset also contains a small number of diversion factors to other modes in urban conurbations, but these derive from one study only.

In terms of trip-purpose, the analysis focuses on commute, leisure and studies that do not make a distinction. Data for other trip purposes are mainly limited to personal business and, for interurban travel, business, visiting friends and relatives and holidays. We found that for diversion to car, compared to the overall average, the diversion factor value was higher for commuters and lower for studies that made no distinction (Table 42).

Most data on diversion from bus is from the UK and most has been collected by reported best alternative. Diversion factors from bus to car obtained from observed behaviour are consistent with the reported best-alternative values (see Table 43).[24]

[24] In Table 43, Appendix B, the data for reported best alternative and transfer method approaches have been combined, as these are methodologically similar and there were only a few data collected by the transfer method.

Table 16: Average diversion factors from bus as intervention mode

Recipient/source mode	Mean diversion factor	N	Standard error
All data			
Car	0.29	63	0.02
Rail	0.36	33	0.04
Light rail/metro	0.19	8	0.08
Cycle	0.06	13	0.01
Walk	0.21	13	0.05
Taxi	0.12	10	0.02
Air	0.08	9	0.02
No travel	0.14	44	0.02
Other	0.07	37	0.01
UK data only			
Car	0.30	51	0.03
Rail	0.36	31	0.05
Light rail/metro	0.19	8	0.08
Cycle	0.05	10	0.01
Walk	0.24	11	0.05
Taxi	0.12	10	0.02
Air	0.08	9	0.02
No travel	0.13	40	0.02
Other	0.07	36	0.01
Journeys in urban areas			
Car	0.30	41	0.03
Rail	0.12	14	0.03
Light rail / metro	0.19	8	0.08
Cycle	0.06	13	0.01
Walk	0.21	13	0.05
Taxi	0.12	10	0.02
No travel	0.15	23	0.02
Other	0.10	18	0.02
Interurban journeys			
Car	0.30	19	0.03
Rail	0.54	19	0.04
Air	0.08	9	0.02
No travel	0.09	19	0.01
Other	0.04	18	0.01

3.3.3. Diversion from car as intervention mode

Seven studies report diversion factors for car as the intervention mode. Diversion factors for each of the eight choice sets these cover are presented with no segmentation in Table 48, Appendix B.

For diversion for car, the recorded data are almost evenly split between urban and interurban journeys, with all the urban data for metropolitan areas. In the urban environment, there is some consistency across choice sets for diversion to bus, walk and not travelling. In general, diversion to rail is low for choice sets that also contain light rail/metro as an alternative, with the two modes acting as substitutes.

Again, the data for interurban journeys comes from Vicario (1999) and Dargay (2010) and shows high diversion from car to rail and very little to coach or air. As discussed in 3.3.1, the two studies report quite different proportions of car users choosing rail or not to travel.

In Table 17, we present the results averaged over all choice sets. These indicate that there is a clear difference in diversion to bus and rail for urban and interurban journeys. Diversion to bus is large in urban areas (0.31) and diversion to rail is small (0.12), whereas the opposite is seen for interurban travel (0.09 bus and 0.65 rail). These reflect the differences in the base shares and availability of the two modes for urban and interurban journeys. The overall average is an average of these extremes, given that there are roughly equal numbers of data points for the two types of journeys. We also note that the interurban averages smooth out the differences between the studies but give higher weight to the Dargay (2010) values, as this study included more segmentation and therefore more diversion-factor data points.

Six of the seven studies report diversion-factor values for commuters, with the remaining study not differentiating by trip purpose. Hence the averages for commuters in urban areas are very similar to the values in Table 17. For other trip purposes, data are mainly taken from the three key studies. Leisure travellers in urban areas change to bus in higher numbers (0.44, se 0.04, N=3) or choose not to travel (0.21, se 0.06, N=3) but these are based on only a few values.

Most data on diversion from car is from the UK and has been collected by reported best alternative, transfer time or transfer price. Diversion factors from car to bus obtained from observed behaviour are consistent with the values reported by the other methods.

Table 17: Average diversion factors from car as intervention mode

Recipient/source mode	Mean diversion factor	N	Standard error
All data			
Bus	0.18	34	0.03
Rail	0.45	32	0.05
Light rail/metro	0.23	8	0.06
Cycle	0.05	7	0.02
Walk	0.09	7	0.02
Taxi	0.08	7	0.03
Air	0.07	10	0.01
No travel	0.16	32	0.02
Other	0.07	26	0.01
UK data only			
Bus	0.18	32	0.03
Rail	0.46	31	0.06
Light rail/metro	0.23	8	0.06
Cycle	0.05	7	0.02
Walk	0.09	7	0.02
Taxi	0.08	7	0.03
Air	0.07	10	0.01
No travel	0.17	31	0.02
Other	0.07	25	0.01
Journeys in urban areas			
Bus	0.31	14	0.04
Rail	0.12	12	0.03
Light rail/metro	0.23	8	0.06
Cycle	0.05	7	0.02
Walk	0.09	7	0.02
Taxi	0.08	7	0.03
No travel	0.16	12	0.03
Other	0.08	8	0.02
Interurban journeys			
Bus	0.09	20	0.01
Rail	0.65	20	0.04
Air	0.07	10	0.01
No travel	0.16	20	0.03
Other	0.06	18	0.02

3.3.4. Diversion from rail as intervention mode

The analysis in this section is based on 18 studies covering 14 choice sets. Diversion factors by choice set are presented in Table 49, Appendix B.

In the choice-set analysis for urban journeys, a wide range of diversion factors for bus and car are reported but the combined share of the modal shift from rail of these two modes is more consistent, indicating that the diversion depends on the availability of these modes. A similar degree of variation can also be seen across choice sets for other modes. As the rail mode incorporates high-speed rail, the diversion factors for interurban journeys include more diversion to air as well as to car than to bus (coach).

Diversion-factor values averaged across choice sets are presented in Table 19. Fifteen per cent of data for diversion from rail was from Australia, Canada or New Zealand. The overall values for the UK are therefore slightly different than those using the full dataset. In particular, the diversion factor to car is higher, and for choosing not to travel is lower for the UK, mainly due to the higher proportion of values for commute trips. However, the UK averages are not significantly different from the overall averages.

Diversion to bus is lower and diversion to car is higher for interurban journeys than for urban journeys. The urban data is almost exclusively metropolitan with no data for urban-conurbations and only 3 data points for small towns. The values for diversion from rail to bus (0.03, s.d. 0.01, N=6) and car (0.53, s.d. 0.06, N=6) in rural areas are based on data for a single study in Aberdeenshire. These suggest diversion to car and bus in rural areas is similar to interurban values, although there is a high degree of variation in the values underlying these averages.

Diversion factors from rail to car and bus by trip-purpose are summarised below.

Table 18: Diversion factors from rail as intervention model to bus and car, by journey purpose

Recipient/source mode	Commute	Business	Leisure	No distinction
Bus	0.16 (0.04)	0.07 (0.03)	0.21 (0.04)	0.30 (0.04)
Car	0.47 (0.04)	0.58 (0.03)	0.46 (0.05)	0.31 (0.04)

* standard error in brackets

Diversion factor data for rail was collected by all three research methods. As can be seen from Table 46 in Appendix B, there is some difference in the values for diversion to bus and car. For car, the values derived from reported best alternative and transfer methods are higher than from observed changes. A more detailed analysis of the other variables underlying these values would be required to discern any systematic differences between the methods.

Table 19: Average diversion factors from rail as intervention mode

Recipient/source	Mean diversion factor	N	Standard error
All data			
Bus	0.22	71	0.02
Car	0.43	71	0.02
Light rail/metro	0.08	9	0.02
Cycle	0.04	14	0.01
Walk	0.01	12	0.01
Taxi	0.04	15	0.01
Air	0.29	15	0.04
No travel	0.17	71	0.01
Other	0.09	46	0.01
UK data only			
Bus	0.23	53	0.02
Car	0.46	53	0.03
Light rail/metro	0.08	9	0.02
Cycle	0.02	10	0.01
Walk	0.02	10	0.01
Taxi	0.05	9	0.02
Air	0.27	11	0.04
No travel	0.14	54	0.02
Other	0.09	46	0.01
Journeys in urban areas			
Bus	0.32	30	0.03
Car	0.35	29	0.03
Light rail/metro	0.10	6	0.02
Cycle	0.04	14	0.01
Walk	0.01	12	0.01
Taxi	0.04	13	0.01
No travel	0.17	28	0.02
Other	0.08	19	0.02
Interurban journeys			
Bus	0.17	31	0.02
Car	0.49	32	0.03
Taxi	0.02	2	0.01
Air	0.29	15	0.04
No travel	0.17	32	0.02
Other	0.05	18	0.01

3.3.5. Diversion from light rail/metro as intervention mode

Ten studies reported diversion factors for an intervention on light rail/metro and over 90% of data were from the UK. Diversion factors for light rail/metro are only available for urban journeys. As can be seen from Table 20, there are differences between diversion to bus, car and rail depending on the urban area type. However, the data for metropolis area types is quite limited, with only 50% from London. Diversion factors are also presented separately by choice set for this mode (Table 50, Appendix B). Diversion to cycle, walk and to a lesser extent choosing not to travel is more similar across all urban forms and choice sets, although the number of observations are quite small (results not shown in summary table for this reason). Six studies contained a 'no-travel' option and the diversion factor for this alternative is consistent with values reported for bus, car and rail in urban areas.

Approximately two thirds of the data for light rail/metro came from observed changes in behaviour and these were more likely to relate to new investments than to improvements or deteriorations in service, as was the case for bus, car and rail. The diversion-factor values appear to be reasonably consistent across the two research methodologies, apart from diversion to car. However, there are few data available for each mode pair calculation for the reported best-alternative approach.[25]

All ten studies reported some diversion factors for which there was no segmentation by trip purpose. In addition four studies reported values for commuting and three for leisure travel. These are reproduced in Table 21 and show that a smaller proportion of commuters divert to bus than for other user types and fewer leisure travellers would take the car. However, given the number and variation in the values, these are not clearly different from the overall values.

[25] These data are not reported here.

Table 20: Average diversion factors from light rail/metro as intervention mode

Recipient/source mode	Mean diversion factor	N	Standard error
All data			
Bus	0.35	26	0.03
Car	0.23	27	0.03
Rail	0.23	22	0.03
Cycle	0.05	9	0.01
Walk	0.03	12	0.01
Taxi	0.08	10	0.02
No travel	0.17	23	0.02
Other	0.03	13	0.01
UK data only			
Bus	0.33	24	0.03
Car	0.24	23	0.03
Rail	0.23	22	0.03
Cycle	0.05	8	0.01
Walk	0.03	12	0.01
Taxi	0.08	10	0.02
No travel	0.16	20	0.02
Other	0.03	13	0.01
Metropolis			
Bus	0.60	4	0.05
Car	0.17	4	0.03
Rail[1]	0.06	1	
No travel	0.18	3	0.05
Metropolitan			
Bus	0.31	22	0.05
Car	0.24	23	0.06
Rail	0.24	21	0.02
Cycle	0.05	8	0.01
Walk	0.03	11	0.01
Taxi	0.08	10	0.02
No travel	0.161	20	0.02
Other	0.05	6	0.01

Values for cycle and walk were also based on a single study.

Table 21: Diversion factors from light rail/metro as intervention mode by journey purpose

Recipient/source mode	Mean diversion factor	N	Standard error
Commute			
Bus	0.30	4	0.08
Car	0.25	4	0.06
Rail	0.23	4	0.10
Leisure			
Bus	0.40	3	0.12
Car	0.19	3	0.03
Rail	0.21	3	0.09
No distinction			
Bus	0.41	12	0.05
Car	0.25	13	0.05
Rail	0.16	8	0.04
Cycle	0.06	7	0.01
Walk	0.03	7	0.01
Taxi	0.10	5	0.03
No travel	0.17	14	0.02
Other	0.04	6	0.01

3.3.6. Diversion from cycle as intervention mode

The analysis in this section is based on seven studies that report on journeys in urban areas for six choice sets. We note that the three key studies discussed in Section 3.3.1 do not contain data for cycle as an intervention mode, although cycle is a recipient/source mode in SYSTRA (2016a) and Vicario (1999). For diversion factors from bicycle, only a small dataset was available and roughly only one third of the data were from the UK. The diversion factor values for this mode presented in Table 22 are therefore largely based on international data. However, analysis of the diversion factors from this mode for each choice set separately (Table 51, Appendix B) indicates a reasonable degree of consistency in the values for diversion to walk across all studies. These values are higher than those obtained for diversion to walk from other modes. The diversion factor from cycle to walk in Table 22 is 0.27 compared with values of 0.21 for bus, 0.09 for rail and 0.02 for light rail/metro respectively, as intervention modes. In addition, while there are differences in the diversion values for bus, car and rail across choice sets, there is less variation in the overall share of these modes in the shift from cycle. This suggests the mode choice between the main modes depends on their relative importance within the particular urban environment. It is interesting to note that the one study that contains a no-travel alternative reports quite a high model shift to this option (0.24).

Only one study looked at commuter behaviour. The others made no distinction by trip purpose.

Table 22: Average diversion factors from cycle as intervention mode

Recipient/source mode	Mean diversion factor	N	Standard error
All data			
Bus	0.26	8	0.06
Car	0.15	7	0.05
Rail	0.19	4	0.08
Light rail/metro	0.16	5	0.07
Walk	0.27	7	0.05

3.3.7. Diversion from air as intervention mode

Dargay (2010) is the only source of data for air as the intervention mode, although air is a travel alternative in Vicario (1999). There is only one choice set for diversion from air, which is for trips over 150km in length. The data have been obtained using transfer price and transfer time methods. The overall averages shown in Table 23 indicate that diversion is mainly to rail and car. As noted in Section 3.3.1, Dargay (2010) reports values for several trip purposes. These are presented in Table 24.

Table 23: Average diversion factors from air as intervention mode

Recipient/source mode	Mean diversion factor	N	Standard error
All data			
Bus[1]	0.03	8	0.01
Car	0.33	8	0.04
Rail	0.51	8	0.04
No travel	0.10	7	0.01
Other	0.01	8	0.01

[1] As noted previously bus is synonymous with coach for interurban journeys.

Table 24: Diversion factors from air as intervention mode by trip purpose

Trip purpose	Recipient/source mode				
	Bus[1]	Car	Rail	No travel	Other
Business	0.03	0.28	0.61	0.10	0.00
Leisure	0.05	0.31	0.50	0.08	0.01
Visiting friends and relatives	0.03	0.52	0.35	0.10	0.00
Holidays/short breaks	0.04	0.22	0.58	0.13	0.04

[1] As noted previously bus is synonymous with coach for interurban journeys.

4. Recommended diversion values

In this chapter we present recommended diversion values for use in transport appraisal and other applications, derived from the detailed results presented in Chapter 3. In order that this chapter can be used without reference to other sections of the report, we first provide a brief overview of the methodology and terminology. We then set out recommended diversion factors for interventions on bus, car, rail, light rail/metro and cycle. These are presented as best-estimate values for a number of representative scenarios and as ranges. For bus only, national averages are also provided. Finally, we compare the new values with existing guidance.

4.1. Overview

Diversion factors quantify the impact of changes on one mode of transport on the demand for other modes and for new trips. In transport appraisal they are used to determine the source and extent of new traffic resulting from an investment. In this case, diversion factors represent the proportion of new traffic on a mode that would otherwise have used another mode or that would not have travelled (generated demand). However, it is also possible that there could be a decrease in demand on a mode due, for example, to a reduction in bus service. In that case, the diversion factor represents the proportion of demand diverted away from bus to other modes or for those that no longer travel. We use the following definitions to make clear how the values presented in this section should be used:

- **Intervention mode**. An intervention occurs **only** on this mode that results in a change in demand. Examples of interventions include: a new investment, a service improvement/deterioration or a policy change, such as a congestion charge.
- **Recipient/source modes**. These are all the modes that are affected by the change in demand on the intervention mode. Demand moves **from** these modes if there is a positive change in demand on the intervention mode. Demand may move **to** these modes if there is a negative change in demand on the intervention mode.

For a given intervention, the intervention mode and the recipient/source modes together make up the **choice set**, which consists of all the possible travel alternatives available to the traveller. Diversion factors **only** sum to one if they take account of the redistribution of demand across all possible alternatives, including not travelling or newly generated traffic.

The recommended diversion factors presented in this chapter are based on analysis of a dataset of 934 values, covering ten possible modes: bus, car, rail, light rail/metro, cycle, walk, taxi, air, generated traffic and other.[26] Values were reported for five intervention modes: bus, car, rail, light rail/metro and cycle. It is not possible to infer diversion factors for interventions on other modes not included in this list, because the diversion factors are not symmetric.[27] In the dataset of values, there were 35 different choice sets across the available evidence, each consisting of between two and ten modes. These have an impact on the magnitude of the diversion factors, both through the number and composition of modes. Variations in the diversion-factor values may also result from differences in area type (where the intervention took place), journey type, trip purpose and study design, as well as unobservable characteristics, including characteristics specific to a particular location. Table 25 shows the distribution of observed data across different segmentations for all modes. Most of the urban data is metropolitan but there is also a large number of interurban journeys and a reasonable spread of values across trip purposes and study design.[28]

Table 25: Main categories of data segmentation (not differentiated by mode)

Segmentation	Categories					
Area Type	Large metropolis: 32	Metropolitan: 471	Urban conurbation: 31	Small towns: 7	Rural: 30	No distinction: 21
Journey Type	Urban: 509	Interurban: 336				No distinction: 84
Trip purpose	Commute: 161	Business: 117	Leisure: 266			No distinction: 275
Study design	Observed: 247	Best Alternative/Stated Intention: 320	Transfer time/price: 463			

To minimise the variation in the data and to reduce the impact of unobservable characteristics, our approach is to use as much data as possible in the calculation of the recommended diversion factors. This means that, for a given intervention mode, data from all possible choice sets are included, with no segmentation unless specified.

[26] These modes have been aggregated from the 23 original possibilities. The 'other' mode encompasses changes in route, destination, journey time and other non-defined alternatives.

[27] By symmetry we mean that the diversion from rail to bus due to an intervention on bus is not the same as the diversion from bus to rail due to an intervention on rail. Symmetry is not the same as equivalence. In that case, if traffic was diverted away from bus to rail and car due to a bus-fare increase, a reduction in fare of the same amount would lead to this traffic returning to bus from rail and car in the same proportions. See Section 3.1 for a more detailed discussion.

[28] More details on the data segmentation can be found in Section 3.2. The area-type classification is explained in Section 3.2.4.

4.2. Recommended values

In this section, we present best-estimate values for a number of scenarios that are considered to be useful for transport appraisal purposes.

Table 26: Recommended diversion factor values for an intervention on bus

Recipient/source mode	National weighted mean	Metropolitan[1]	Metropolitan (no light rail)	Metropolitan commute	Urban-conurbation[2]
car	0.24	0.25	0.30	0.30	0.30
rail	0.11	0.11	0.14	0.07	0.10
light rail	0.16	0.18		0.25	
cycle	0.04	0.06	0.07	0.07	0.04
walk	0.14	0.18	0.22	0.14	0.26
taxi	0.12	0.10	0.12	0.07	0.13
no travel	0.19	0.12	0.15	0.10	0.17
N[3]		94	86	19	25

Source: New analysis. [1] Data for metropoles (e.g. London) are combined with metropolitan. [2] There are no light rail data for urban conurbations. [3] N denotes the number of data points used to calculate the average.

Table 27: Recommended diversion factor values for an intervention on car

Recipient/source mode	Metropolitan	Metropolitan (no light rail)	Metropolitan commute	Interurban
bus	0.30	0.39	0.29	0.09
rail	0.11	0.14	0.10	0.67
air				0.07
light rail	0.22		0.29	
cycle	0.05	0.06	0.06	
walk	0.08	0.11	0.08	
taxi	0.08	0.10	0.05	
no travel	0.16	0.20	0.13	0.17
N	67	59	22	70

Source: Table 17. N denotes the number of data points used to calculate the average.

Table 28: Recommended diversion factor values for an intervention on rail

Recipient/source mode	Metropolitan	Metropolitan (no light rail)	Metropolitan commute	Urban-conurbation
bus	0.31	0.35	0.22	0.15
car	0.33	0.37	0.44	0.44
air				0.26
light rail	0.10		0.08	
cycle	0.04	0.04	0.01	
walk	0.01	0.01	0.01	
taxi	0.05	0.05	0.05	
no travel	0.16	0.18	0.19	0.15
N	129	123	25	112

Source: Table 19. N denotes the number of data points used to calculate the average.

Table 29: Recommended diversion factor values for an intervention on light rail/metro

Recipient/source mode	Metropolitan	Metropolitan commute
bus	0.31	0.26
car	0.20	0.22
rail	0.20	0.20
cycle	0.05	0.05
walk	0.02	0.04
taxi	0.07	0.10
no travel	0.15	0.13
N	129	19

Source: Table 20 and new analysis. Most data on light rail comes from studies of Greater Manchester. Commute data are from one study only. N denotes the number of data points used to calculate the average.

Table 30: Recommended diversion factor values for an intervention on cycle

Recipient/source mode	Metropolitan	Metropolitan (limited choice set)
bus	0.19	0.25
car	0.11	0.15
rail	0.14	0.18
light rail	0.12	0.16
walk	0.19	0.26
taxi	0.08	
no travel	0.17	
N	33	

Source: Table 22. Values based on only one data point for taxi and no travel.

How the values are calculated

For some modes, there are sufficient data to calculate diversion factors for different segmentations of interest. In particular, we can distinguish choice sets with and without light rail, commute trip purpose and metropolitan and urban-conurbation area types. For car and rail we also include urban and interurban journey types with air as an alternative.[29] For some calculations, data from tables in the main report are used directly. For others, additional analysis of the dataset has been undertaken.

In all cases, diversion factors for each intervention mode have been calculated according to the following methodology:

- We include the full set of alternative recipient/source modes for which data are available. This includes generated traffic (or equivalently, trips no longer made) but excludes 'other' modes. This is because for some datasets it is not clear what this mode covers, while for others it covers a wide range of possibilities that may not be relevant in most settings.
- The diversion factors are normalised so that they sum to one across the full set of alternatives.[30]
- For the two types of metropolitan areas considered – one with a light rail/metro alternative and one without – diversion factors are calculated from the same set of data. For the metropolitan area without light rail, the diversion factor for this mode is discarded before normalisation.[31]

For bus as intervention mode only, it was possible to calculate a weighted national mean-diversion factor. This covered all journeys made in urban and rural areas, excluding interurban journeys. The diversion factors for the different area types were weighted by the number of trips undertaken in each area type. There were insufficient reported data from area types other than metropolitan to make this calculation for other modes.

How to use the tables

The values presented in Table 26 to Table 30 represent the recommended values and can be used in transport appraisal applications in the following ways. We use Table 26 with bus as the intervention mode as an example.

[29] There are data on coach travel in the tables in the main report but these are not the focus of the representative scenarios presented in this section.

[30] Consider an example where diversion factors from bus, to car, rail and no travel are 0.3, 0.2 and 0.2 respectively and only these three alternative modes are available. The total before normalisation is 0.7 (0.3+0.2+0.2). Normalising means that each diversion factor is multiplied by the same amount (1/0.7 in this case) so that the sum of the diversion factors over all possible alternatives is equal to 1. The new diversion factors from bus (for the choice set: bus, car, rail, no travel only) are 0.4, 0.3 and 0.3 respectively (calculated to 1 decimal place only). The same approach is used if the sum before normalisation is greater than unity; here the multiplier will be less than one.

[31] The alternative approach is to restrict the analysis to (sub)studies that do and do not include light rail/metro, respectively. However this is found to be too limiting in terms of available data and studies and hence may not generate values that are applicable to most metropolitan areas.

1. If the set of possible alternatives in the application is the same as the recipient/source modes listed in the table, and the area type corresponds to one of the columns, then values can be read directly from the table. For example, column 4 corresponds to a bus intervention in a metropolitan area without light rail, for all journey types and for car, rail, cycle, walk, taxi and no travel as alternative modes. The diversion factors sum to one.
2. For the above case, if the choice set contains a mode that is available in the local context, but is not considered relevant for the appraisal application, values for the other modes can still be read directly from the table. The values will sum to less than one. For example, if cycle is a possible alternative but it is not of interest for the appraisal of a particular policy, it should still be included in the calculations but not be reported (e.g. diversion factors will sum to 1 minus 0.07, the value for cycle).
3. If the set of possible alternatives in the application does not cover all the recipient/source listed in the table, but the area type corresponds to one of the columns, then the values reported in Table 26 can be renormalised over the appropriate choice set. For example, if the choice set for an urban conurbation did not contain cycle or walk alternatives, the values from column 6 are reweighted by the sum over car, rail, taxi and no travel (0.70) to sum to one. The reweighted values for car would then be 0.42 (=0.29/0.7).

For users interested in other segmentations by area type (e.g. all urban areas together), or indeed for particular choice sets, the two main principles used above can be applied to data from the tables in Section 3.3 and Appendix B. All the tables consist of aggregated data, except where data were only available from one (sub-)study and the diversion factors do not necessarily sum to one.

- The full set of modes that are available need to be taken into account, even if these modes are not all of interest and will not be reported in the application. This also includes generated traffic (or equivalently, trips no longer made) unless the trip purpose is considered non-discretionary (e.g. commuting).
- Diversion factors should sum to one across the full set of alternatives and should not exceed one. They can sum to less than one if diversion factors are not reported for all possible alternatives.

The numbers and types of diversion factors that can be calculated from the dataset are limited by the availability of reported data. As noted earlier, it is not possible to calculate diversion factors for interventions on some modes or for all trip purposes or area types because the dataset does not contain values for these.

For cycle as an intervention mode, the values presented in Table 30 are based on limited data. It is recommended that, where possible, the most appropriate choice set is selected from Table 51 (Appendix B) and the normalisation process applied. However, diversion factors from both tables should be used with caution.

It is important to note that the above central estimates are normalised averages over a range of data and should not imply precision not present in the data, given the number of dimensions, such as trip purpose, area type and study design, across which data have been reported. Below we present recommended ranges of diversion factors for interventions on bus, car, rail, light/rail/metro, cycle and walk. These reflect the uncertainty in the data (approximately the 95% confidence intervals). The reference ranges in Table 31 provide a summary of the detailed analysis presented in the tables in Section 3.3 and in Appendix B. It is recommended that any values used in appraisal applications are checked against Table 31.

Table 31: Recommended diversion factors for interventions on bus, car, rail, light rail/metro and cycle

Intervention mode	Recipient/source mode						
	Bus	Car	Rail	Light rail / metro	Cycle	Walk	Generated traffic (no travel)
Bus		All trip purposes: 0.20-0.35 Commute: 0.30-0.55	Urban areas: 0.05-0.2 Intercity: 0.45-0.65	Urban areas: 0.05-0.35	Urban areas: 0.04-0.08	Urban areas: 0.1-0.3	Urban areas: 0.10-0.20 Interurban: 0.07-0.11
Car	Urban areas: 0.20-0.40 Interurban: 0.07-0.11		Urban areas: 0.05-0.20 Interurban: 0.55-0.75	Urban areas: 0.10-0.35	Urban areas: <0.1	Urban areas: 0.05-0.15	Urban areas: 0.1-0.25 Interurban: 0.10 - 0.25
Rail	Urban areas: 0.25-0.4 Interurban: 0.1-0.2	Urban areas: 0.3-0.45 Interurban: 0.4-0.55		Urban areas: 0.05-0.15	Urban areas: <0.1	Urban areas: <0.05	Urban areas: 0.10-0.20 Interurban: 0.10-0.20
Light rail/metro	Urban areas: 0.25-0.4	Urban areas: 0.15-0.3	Urban areas: 0.15-0.3		Urban areas: < 0.1	Urban areas: < 0.05	Urban areas: 0.10-0.20
Cycle	0.150.05-0.4, higher for walk and bus						

4.3. Comparison with current guidance

We now briefly compare our findings and recommendations with current guidance, which is summarised in Table 32. The values are presented as shown in TRL (2004) with the intervention modes – bus/coach, car and rail – in the first column. We note that there are no values for light rail/metro and cycle and walk as separate modes in the current guidance. The values for other modes are based on a small number of studies or are generated by a model.[32] As the guidance values are normalised to sum to one over a smaller set of modes, we would, in general, expect them to be higher than the values reported here.

We find that, for most modes, the diversion factors in the guidance either fall within the range of values shown in Table 31 or are higher than these values, as expected for a smaller choice set. Where there are exceptions, these can mostly be explained by differences in the datasets on which the reported values are based.

For bus interventions in urban areas, current guidance values fall within our proposed ranges for car and rail, with generated traffic only slightly higher. The combined diversion factor for cycle and walk exceeds our proposed values. In our dataset, while Vicario (1999) has a large shift to walk for all trip purposes considered, other studies, notably SYSTRA (2016a) report much smaller values. For interurban journeys, our findings are consistent with current guidance for diversion to car and rail, but we find less generated traffic.

For car interventions in urban areas, current guidance on diversion to rail is higher than our proposed range for rail alone, but falls within the combined rail/light-rail range. Further, the choice sets in Appendix B that do not have light rail as an alternative report values of 0.24–0.27. Diversion to bus in Table 32 is higher than suggested by our dataset, while cycle/walk and generated traffic fall within the range. For interurban journeys, diversion to rail is lower than suggested by our dataset, and generated traffic is higher. Vicario (1999), on which current guidance is based, reports high generated traffic while Dargay (2010) reports a lower share. Both studies are used in our analysis.

For rail, current values for diversion factors to bus for urban rail journeys are higher than our findings suggest. Interurban diversion from rail is more consistent. The diversion factors from the National Transport Model do not report generated traffic and cover modes found in urban areas. The values are generally consistent with our findings for urban areas, although the diversion from rail to walk is higher than our study would suggest and from rail to bus is lower.

[32] In TRL (2004), the number of studies is reported as between two and four, and these include Vicario (1999).

Table 32: Recommended diversion factors for interventions on bus, car, rail, light rail/metro and cycle[33]

			Urban		
Mode to/from	Bus	Car	Rail	Cycle/Walk	Generated
Bus		0.31	0.06	0.42	0.21
Car	0.48		0.24	0.06	0.22
Rail	0.41	0.33		0.01	0.24
			Interurban		
	Coach	Car	Rail	Air	Generated
Coach		0.22	0.60		0.18
Car	0.10		0.42	0.01	0.47
Rail	0.20	0.60		0.06	0.14
			National Transport Model		
	Bus	Car driver	Car passenger	Cycle	Walk
Rail	0.16	0.44	0.24	0.04	0.13

Data are presented as percentages in original sources. We use Table C2 from WebTAG A5.4 as 99.5% of data in our study is trip based. Row values sum to one, except for NTM values for rail.

[33] There appears to be some confusion in the translation of the original evidence on which the current guidance is based, particularly in the interpretation of what modes the traffic is coming from and where they are going to. For example, the current WebTAG advice indicates that 41% of traffic attracted to rail, as a result of improved rail services, would come from bus. However, the values in the original evidence report the opposite, i.e. that 41% of new traffic on improved bus services would come from rail.

5. Evidence on bus fare elasticities

This chapter summarises the latest bus-fare elasticity evidence.

5.1. Background: current WebTAG guidance

The Department for Transport's current recommendations are set out in section 6.4.24 of WebTAG unit M2 (DfT 2017). We reproduce the relevant section here:

'Elasticities of bus trips with respect to bus fares for full fare paying passengers have been found to lie typically in the range –0.7 to –0.9 for changes over a period longer than 5 years (Dargay & Hanly). Unless analysts can provide a good reason otherwise, the Department's view is that the annual average bus fare elasticity from the base year model should lie within this range. It should be noted that up to a third of bus trips made in the off-peak and some in the morning peak are made by concessionary passengers free of charge. Their demand will be unaffected by changes in fares. If possible, it would be useful to estimate the fare elasticity for full fare paying passengers separately noting that there are several half-fare or similar schemes for children and students. Including concessionary passengers would tend to reduce the elasticities given above to around –0.4 with a lower elasticity in the off-peak.'

The relevant section of Table 6.1 from Section 6.4.25 (WebTAG Unit M2 (DfT 2017)) is reproduced below. It is stated that these 'may also be useful in addition to the elasticities given in this Section.' However, the provenance of these elasticities is unclear, except for their use in multi-modal studies, and they are not explicitly stated to relate to the whole market. We would point out though that a ten-year adjustment is somewhat longer than apparent in dynamic econometric models of bus demand.

Table 33: Bus fare elasticities (reproduced from WebTAG Unit M2, Table 6.1 (DfT 2017))

Expected short- and long-term bus-trip kilometre fare elasticities			
	High	Central	Low
1 year	-0.65	-0.3	-0.16
5 years	-0.96	-0.6	-0.38
10 years or longer	-1.12	-0.7	-0.44

5.2. Evolution of the conventional wisdom

The earliest convention regarding bus-fare elasticities was the 'Black Book' (Bly et al. 1980) recommendation of –0.3, which was regarded to be a short-run value with long-run values not separately distinguished. The study did recognise that this was an average, and variations could be expected with regard to factors such as time of day and purpose.

The major review of Goodwin (1992) focused on the distinction between short- and long-run elasticities, with the former little different to the prevailing conventional wisdom of –0.3 and a long-run value of around –0.6.

Dargay & Hanly (1999) concluded on the basis of a range of evidence that 'The most-likely values for the fare elasticity for Great Britain as a whole are about –0.4 (±0.1)[34] in the short run and –0.9 (±0.1) in the long run.'

The major update to the Black Book (TRL 2004) conducted an extensive review of bus-fare elasticity evidence. It found the average short-run bus fare elasticity to be –0.42 with a corresponding long-run value of –1.01. These values support the higher valuations adopted by the Department for Transport as official guidance.

While there could have been several factors at work over the time period that influenced bus-fare elasticities, including a change in the blend of journey purposes, real bus fares tended to increase and this could be expected to exert an upward pressure on elasticities.

We note, however, that the story ends in 2004. Official guidance is based on, and supported by, studies from the 1990s and before based on data that, of necessity, is even older[35] – reflecting a bus market that has somewhat different characteristics than those which now prevail.

5.3. Recent developments

A key feature of the bus market in Great Britain is that it has, over more recent times, experienced significant changes that can be expected to have had impacts on bus-fare elasticities, both for the whole market and for those paying fares.

Over the 1980s and 1990s, the proportion of overall demand formed by concessions was fairly stable. Since 2000, half-price travel has been guaranteed in England while in Scotland and Wales free off-peak travel was introduced. Some local authorities in England provided free travel, some had a flat fare and some had half fares, and some varied what discounted rates and prices they offered over the period. Most significantly though, nationwide free bus travel has been available since 2008.[36]

[34] 95% confidence interval.

[35] Data are often time series, so could be from 1980s or even 1970s.

[36] The English National Concessionary Travel Scheme (ENCTS), introduced in 2008, provides free off-peak travel on local bus services for older and disabled travellers, linked to pensionable age. Scotland, Wales and Northern Ireland have separate schemes.

The major changes in the composition of the market brought about by enhanced concessions will have had impacts on how the bus market in its entirety responds to fare changes. Given that there has been an increase over time in the proportion who travel for free, and hence who have no sensitivity to fare changes, the market elasticity should exhibit a downward trend over time.

The bus-fare elasticity evidence obtained from econometric analysis tends to relate to the whole market, given that the data used covers the total number of boardings and average revenue. Clearly, as recognised in the WebTAG statement reproduced earlier, it would be desirable to estimate elasticities for the full-fare paying market and the concession market.

We might expect a number of developments over recent years to impact on the elasticity of full-fare bus travel:

- The increases in real bus fares over time would be expected to exert an upward pressure on the fare elasticity. However, countering this is that those most sensitive to fare will be more likely to leave the market, while the remainder have a lower average elasticity.
- Higher levels of car ownership, aggressive competition from private-hire taxis and moves towards healthier means of travel would be expected to increase the sensitivity to bus fares.
- The commuting and leisure markets can be expected to have different elasticities. If the journey purpose composition varies over time, in response to employment, income and fare trends, then the overall elasticity will vary.
- The recession and subsequent austerity measures may have had disproportionate impacts on bus users, therefore increasing price sensitivity. Nonetheless, generally increasing incomes might be expected to reduce price elasticities, all else being equal.
- Bus travel might be increasingly dominated by those with fewer transport alternatives, and such dependency might reduce price sensitivity. Nonetheless, to the extent that these individuals are those with lower incomes then price sensitivity might not fall.
- There have been significant developments in the range of bus tickets on offer, some due to competition between operators. Day and period tickets are increasingly popular, while other variants cover permitted operators, modes, areas and times of day. Some tickets place no restrictions on transferability. The availability of more tickets can be expected to influence elasticities; for example, some will appeal to more price-sensitive travellers although others will benefit from lower fares, while period tickets lead to greater loyalty to bus on marginal journeys. Importantly, the ability to switch between tickets when there are fare increases can be expected to reduce the overall demand response to fare increases.
- Improvements in bus service quality might increase willingness to pay.

We do not feel that it is inevitable that the elasticity of the full-fare bus market will have increased over time; it is essentially a matter for empirical investigation.

5.4. The key evidence

The main study regarding bus-fare elasticities remains Dargay & Hanly (1999). Since the work of Dargay & Hanly (1999) upon which the Department for Transport WebTAG guidance is largely drawn, there have been major changes to the local bus market in Great Britain with a larger proportion of concessionary travellers. There have been two significant review studies since then, and one study that essentially updates Dargay & Hanly (1999).

As part of this review study, we have not uncovered any new British empirical evidence on bus fare elasticities.

5.4.1. The work of Dargay & Hanly (1999)

This major DfT-funded study used STATS100 data at national, regional and county level.[37] The national data covered 1977 to 1996, 1987 to 1996 for regional data and 1987 to 1996 for county-level data. Note that these data cover all demand for bus travel; it is not possible to distinguish the concessionary and non-concessionary demand, which can be expected to have different elasticities.

In addition, Passenger Transport Executive (PTE) survey-based demand data was obtained expressly for the purpose of estimating elasticities for the adult full-fare paying market segment. This covered the period 1987 to 1998.

The national data obtained an overall market elasticity of around –0.3 in the short run and around –0.7 in the long run[38].

Elasticities were estimated at regional level, such as London, metropolitan, shire counties, Scotland and Wales, with additional segmentation of the metropolitan counties. The variations obtained were not entirely convincing. At an overall level, the regional data provided a short-run elasticity of –0.22 and a long-run elasticity of –0.81. The metropolitan areas yielded short- and long-run fare elasticities of –0.24 and –0.45 but with considerable variation across the six specific areas.

When models were estimated at the county level, there was considerable variation across counties, although only 22 of the 46 estimated fare elasticities were significant. The short-run elasticity averaged around –0.4 and the long-run averaged around –0.8.

For the PTE data, the estimated fare elasticities were:

- Total Journeys: –0.24 short run and –0.52 long run
- Full Fare Journeys: –0.15 short run and –0.38 long run

This study pre-dates free concessionary travel, although reduced fare schemes were in place for the elderly. The general feeling was that the concessionary market was more price sensitive at a given fare level because of lower incomes and because the trips made were more optional. However, offsetting this is the lower fares paid by the elderly.

While these results indicate that full-fare paying passengers are less sensitive than the market as a whole, and hence somewhat less sensitive than the concessionary market, the elasticities for full and total journeys

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[37] STATS100 is a DfT database of bus operators' annual returns, and states – amongst other metrics – the total number of passenger boardings, bus kilometres and ticket receipts.

[38] In this study, short run is one year, which is the periodicity of the data, and the long run tended to be around five years.

were not significantly different. This was attributed, in part, to a 'number of inconsistencies' in the survey-based data while the data set is small. This might also explain why the elasticities estimated for the whole market were less than those obtained using STATS100 data.

In conclusion, Dargay & Hanly (1999) recommended the bus-fare elasticities for **full-fare** passengers presented in Table 50.

Table 34: Dargay & Hanly (1999) recommended full-fare elasticities

	Short Run	Long Run
Great Britain	-0.2 to -0.3	-0.7 to -0.9
England	-0.2 to -0.3	-0.6 to -0.8
Non Urban	-0.2 to -0.3	-0.8 to -1.0
Urban	-0.2 to -0.3	-0.4 to -0.6

An element of uncertainty is the impact that the concessionary market will have had on elasticities estimated for the whole market, and hence the applicability of the latter to the full-fare market.

The Dargay & Hanly (1999) research provides a number of other important insights. It provides evidence that, as might be expected, the bus-fare elasticity varies with the level of bus fare. There are also variations between area types (e.g. counties), which might reflect variations in competition and the quality of the bus service offering, and there was some evidence that fare elasticities are slightly larger for increases than reductions in fare.

5.4.2. Demand for Public Transport Update 2004

This was an update to the Webster & Bly (1980) international review of the demand for public transport, sometimes referred to as the 'Black Book'.

The review of bus-fare elasticities took three forms: firstly, a classic literature review and discussion of the available evidence; secondly, a meta-analysis of price elasticities, which turned out to be a forerunner of Wardman (2014), which is discussed below; and finally, a consideration of studies dealing with specific and sometimes niche topics.

The distinction between short- and long-run established in the major Goodwin (1992) review was maintained. The review found that the average short-run bus-fare elasticity had increased to –0.42 with a corresponding long-run value of –1.01. The mean short-run elasticities for peak and off-peak were reported as –0.26 and –0.48 but there was very little variation between London and Non London bus services. The studies reviewed by Goodwin (1992) are, however, now rather dated.

5.4.3. The work of Toner et al. (2010)

The primary purpose of this study was to examine the economics of and reimbursements involved in the concessionary bus market. As part of the study, it conducted what seems to be the most up-to-date analysis of bus demand data that is in the public domain.

The authors use the same STATS100 data set as Dargay & Hanly except with more recent data. The analysis covers 18 years between 1989/90 and 2006/07.

A central hypothesis was that 'there are strong *a priori* reasons for the estimated fare elasticities being lower than those found in previous studies. This is because there has been an increase over time in the proportion of passengers which pay fixed or zero fare.'

For the same county model as estimated by Dargay & Hanly (1999), the short- and long-run elasticities compare as set out in Table 35. The findings strongly support the hypothesis advanced that the whole market bus-fare elasticity will have fallen over time. In addition, models that estimated separate fare elasticities by different time periods clearly demonstrated that as more years are added, the fare elasticity falls. A model that interacted the bus-fare elasticity with a time trend showed the same effects.

Table 35: Comparable recommended whole market elasticities

	Short Run	Long Run
Toner et al. (2010)	-0.18	-0.38
Dargay & Hanly (1999)	-0.33	-0.71

The study went on to explore a wide range of variations in the estimated bus-fare elasticities, according to factors such as area type and population density. The fare elasticity was found to fall with increases in fare. This counter-intuitive effect was attributed to the analysis having to aggregate across the concessionary and full-fare markets.

Of particular interest is an attempt to decompose the whole-market elasticity into elasticities for concessionary and non-concessionary travel. The authors point out that where fares in two sub-markets have varied in opposite directions, as is the case here, the implied overall market elasticity can be lower than the elasticities for each of the sub-markets.

A procedure for decomposing the whole-market elasticity was developed. It relies on an assumption of the relationship between the concessionary and full-fare elasticities: that the elasticities followed a dampened exponential with respect to fare, and the concessionary elasticity is 20% greater than the full-fare elasticity at any given fare. Moreover, the calculations were performed for a period (1997–2003) when fares in both markets were moving in the same direction and the difference between the whole market and deduced full-fare elasticity would be expected to be larger where the full and concessionary fares were moving in different directions, as after 2003.

There are a number of uncertainties surrounding the method, which are acknowledged by the authors. Given these caveats, the decomposed fare elasticities were in the range –0.28 to –0.44 over the time period for the short-run full fare elasticity. These are broadly in line with the Dargay & Hanly (1999) recommendations concerning short-run fare elasticities for full-fare paying passengers.

In summary, for the **whole** market, and using the same modelling approach and data source, albeit with more recent data, this study finds lower elasticities than Dargay & Hanly. This is attributed to the increased proportion paying zero fares. Note, however, that even this more recent data pre-dates the introduction of the nationwide free-fare concessionary scheme, whereupon the divergence in the whole-market elasticities might now be expected to be even larger. As for the **full-fare** market, but with caveats surrounding both the Dargay & Hanly and the Toner et al. analyses, the bus-fare elasticities are broadly in line.

5.4.4. Wardman (2014) review and meta-analysis

Wardman (2014) reports an extensive meta-analysis of UK evidence on fare elasticities. It covered 1,633 elasticities estimated between 1968 and 2010, with 377 (23%) of the observations relating to bus travel. Of these, 82% were based on demand data that provide little insight into elasticity variation by purpose or time period. The mean short-run bus-fare elasticity was –0.45 (±13%[39]) across 83 observations with a mean long-run elasticity of –0.62 (±13%) over 60 observations. The former figure is broadly in line with other evidence and official recommendations, but the latter is a little lower. Note though that some old evidence was covered, with only 14% relating to the period 2001–2010.

The review relied upon evidence from choice models for disaggregated values, but it is not entirely clear whether the elasticity relates to the short run or long run, or somewhere in-between. Commuters were found to have a mean fare elasticity of –0.35 (±23%), with the leisure values only a little larger at 0.41 (±20%). The figures for peak and off-peak travel exhibited more variation, at –0.34 (±18%) and 0.55 (±15%) respectively.

Wardman (2014) estimates a meta-model to explain variations in elasticities across studies. This found elasticities to depend on a wide range of factors, such as mode, data type, journey purpose, short or long run and area type. The model detected that the bus-fare elasticity would increase with the DfT bus fare-index. However, the effect was small; prior to bus deregulation in 1985 the index in metropolitan areas was 48.32 and the increase to 100 in 2010 would imply only a 5per cent increase in the bus-fare elasticity.

The bus-fare elasticities implied by the meta-model for 2010 are reproduced in Table 36. The commuting, in particular, and indeed the leisure elasticities relate largely to full-fare paying passengers given the source of the commuting and leisure evidence. The commuting and leisure short-run elasticities vary a little across areas, although it is perhaps surprising that London elasticities are not lower, and as expected the commuting elasticities are lower.

Taken overall, the short-run elasticities are a little larger than the Dargay & Hanly (1999) recommendations for full-fare elasticities, but strongly support the short-run recommendations of Toner et al. (2010). Long-run commuting and leisure elasticities implied by the meta-model very much support the recommendations of Dargay & Hanly (1999), upon which official recommendations are based.

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[39] 95% confidence interval expressed as a proportion of the central estimate.

Table 36: Implied bus fare elasticities from Wardman (2014) meta-analysis

		PTE	urban	London	Rural
Commute	SR	-0.32	-0.34	-0.42	-0.42
	LR	-0.64	-0.68	-0.83	-0.83
Leisure	SR	-0.42	-0.45	-0.55	-0.55
	LR	-0.84	-0.89	-1.09	-1.09
Leisure Senior Full	SR	-0.72	-0.76	-0.93	-0.93
	LR	-1.43	-1.51	-1.86	-1.86
Leisure Senior Concession	SR	-0.25	-0.27	-0.33	-0.33
	LR	-0.51	-0.53	-0.66	-0.66

Notes: SR = short-run, LR = long-run

The study also distinguished elasticities for the elderly market, providing separate implied elasticities where the elderly paid full and concessionary fares. As expected, the elasticities are lower where the fares are lower and somewhat larger than for the non-elderly market where full fares are charged.

While the evidence tends to support official recommendations, it has to be borne in mind it is somewhat dated.

5.4.5. Other evidence

As part of this review, we uncovered two studies that we were not otherwise aware of.

Tsai et al. (2014) use household travel survey data for Sydney covering 1997 to 2009 to estimate the impact of a number of variables on public transport demand. They recover short- and long-run price elasticities of –0.21 and –0.25 respectively. However, we note that this is for public transport use in general and not just bus travel, while the context is somewhat different to general bus travel in Britain. Moreover, the data covers different people in different years and hence is not ideal for determining the effects of changes in price on demand. Indeed, this might have contributed to the 'atypically' small difference between the long-run and short-run price elasticity, while we should point out that, with a 95% confidence interval of ±71% of the central estimate, the short-run price elasticity is not precisely estimated.

Preston & Almutairi (2014) report models estimated using Transport Statistic Great Britain data. These relate to trips in London over a period since 1991 and trips outside London, distinguishing metropolitan areas, shire counties, Scotland and Wales, for data between 1980 and 2008.

The London model returns a short-run fare elasticity of –0.43 and a long-run elasticity of –0.93. These are for the whole market and are larger than the Dargay & Hanly (1999) figures for urban areas. A possible reason is that there are more alternatives to bus in London and hence larger elasticities, although the relatively low bus fares and high incomes would tend to work in the other direction.

Of more interest here is the model reported for non-London areas, which is based on 101 observations. The short-run fare elasticity is –0.12 and the long-run fare elasticity is –0.34. Given that the model covers the whole market and contains only a few years of free travel, these elasticities seem low. We note that the model contains other terms that might well be correlated with bus fare. These are personal disposable income, which had very large short- and long-run elasticities of –0.63 and –1.70 respectively, while there is also the positive time trend of a 1.1% annual growth in bus demand. Both these sets of figures seem surprising and would cast some doubt on the fare elasticities reported.

In summary, we are of the view that this additional evidence does not provide a strong challenge to existing recommendations.

5.5. Conclusions and recommendations regarding bus fare elasticities

As part of this study, our literature search and requests from key academics, practitioners, operators and authorities have not yielded anything more recent than the Toner et al. (2010) study. The latter study is not used as a basis for official recommendations. Instead, WebTAG guidance is based on the earlier work of Dargay & Hanly (1999). Nonetheless, the Toner et al. (2010) recommendations for short-run fare elasticities[40] for the full-fare market are very much in line with the equivalent Dargay & Hanly (1999) recommendations, thereby supporting official guidance. The major review study of Wardman (2014) also finds the bus-fare elasticities to be in line with these two studies and official guidance.

The story of bus-fare elasticities in Great Britain is that there has been an upward trend over time. This tends to be attributed to increasing real fares. Although there is compelling evidence that the fare elasticity for the whole market has fallen in the 1990s and 2000s, this can be attributed to the increasing share of concessionary travel, which will have lower – and indeed in recent years, zero – sensitivity to fares.

In summary, although the Dargay & Hanly (1999) evidence upon which official guidance is based is dated, and we have offered several reasons why elasticities in the full-fare market might have varied over time, we recommend that these elasticities are maintained as official guidance on the grounds that:

- More recent evidence from the Toner et al. (2010) study and the Wardman (2014) meta-analysis broadly confirm the official elasticities.
- The latter two studies do not themselves contain what might be regarded as up-to-date evidence.

While we recommend that the overall fare elasticities recommended by the DfT should remain unchanged, it is possible to provide more detail. Based on the Wardman (2014) meta-analysis, and reported in Table 30, we would recommend the following disaggregations:

[40] The study reported only short-run elasticities.

Table 37: Recommended values for bus fare elasticities

Overall[1]	LR	-0.7 to -0.9	
Segmentation		Urban	London and rural
Commute	SR	-0.30	-0.40
	LR	-0.65	-0.85
Leisure	SR	-0.40	-0.55
	LR	-0.85	-1.10

Notes: [1] 6.4.24 of WebTAG unit M2 (DfT 2017); LR = long-run, SR = short-run

Further, while there is a consistency in the empirical evidence concerning the fare elasticity in the full fare market, which is of primary interest, we have to recognise that this evidence is dated and much has happened in the bus market and its broader environment more recently. We also have to recognise that the evidence base is not as robust as we might like because of the difficulties involved in disentangling the concessionary market.

It is therefore timely to revisit the demand for bus travel and its fare elasticity since the last major study in 2010. The estimation needs to focus on the full-fare market; the presence now of a sufficiently long time series where concessionary travel has been free does help matters. Possible ways forward are:

- Obtain data that separately identifies full fare, child and senior concessionary travel so that fare elasticities can be estimated in the two markets where fares are paid. Our understanding though is that STATS100 data does not permit this, so other data should ideally be sourced.
- Analyse STATS100 data for the whole market, and then either use the decompositional method of Toner et al. (2010) or else assume that the proportion of the market made up by concessions will remain constant over time, and hence use the whole-market elasticity going forward.
- Obtain fare indices to complement the STATS100 revenue data and model revenue – which does not contain concessionary travel – as a function of the full-fare index. The resulting full-fare revenue elasticity can be converted to a fare elasticity by subtracting one.

In all this, it is worth remembering, as previous studies have shown, that the bus-fare elasticity is not a single number. There should be appropriate consideration of elasticity variations according to the fare charged, local market conditions, area type and other factors that can be investigated that might impact on bus-fare elasticities.

6. Evidence on bus time elasticities

6.1. Background: definition of bus time elasticities

Just as bus demand can respond to variations in fare levels, so it can be influenced by changes in journey times. Bus journey-time elasticities denote the proportionate change in demand after a proportion change in some measure of journey time, of which there are various forms. The journey time might be the overall journey time, in-vehicle time (IVT), walk time or wait time, or indeed some weighted aggregation of the three components of overall journey time into a composite term commonly referred to as Generalised Journey Time (GJT)[41]. There has been far less research into bus journey-time elasticities of all types than into fare elasticities, and this is presumably because in-vehicle times vary somewhat less than bus fares, while it is less straightforward to determine the journey-time variations that have occurred than to specify actual variations in bus fares.

The scope here from the objectives set out in Table 1 is what is termed Generalised Journey Time. The concept of GJT is used in transport planning and appraisal and indeed the Invitation To Tender makes specific mention of GJT in official guidance (Department for Transport, 2017). GJT is composed as:

$$\text{GJT} = \text{IVT} + w_1 * \text{Wait Time} + w_2 * \text{Walk Time} \tag{1}$$

The weights w_1 and w_2 convert wait and walk time into equivalent units of in-vehicle time (IVT). In principle, GJT could be extended to include other time-related attributes, such as average lateness or the degree of crowding, and wait time could be replaced with a measure of service frequency. The formulation above seems most common. If fare is included, then the measure has to be converted either into money – called Generalised Cost (GC) – or time – called Generalised Time (GT) – units, using the travellers' values of time. The GC/GT elasticity is the sum of the fare elasticity and the GJT elasticity.

We can deduce the GJT elasticity from the GC elasticity according to the proportion of GC formed by GJT:

$$\text{GJT elasticity} = \text{GC elasticity} * (\text{value of time} * \text{GJT}) / \text{GC} \tag{2}$$

[41] GJT contains only time elements and should be distinguished from Generalised Time (GT), which additionally contains the monetary elements of travel and is the time equivalent of Generalised Cost.

Other useful relationships are:

GJT elasticity = fare elasticity * value of time *(GJT/fare) (3)

By the same token, we can derive the IVT elasticity as:

IVT elasticity = fare elasticity * value of time *(IVT/fare) (4)

These relationships can be used to derive GJT/IVT elasticities but a potential problem is that the GJT/IVT elasticity depends upon the ratio of GJT/IVT and fare and hence can vary widely. Analogous relationships exist between the GJT/IVT elasticity and the GC/GT elasticity.

We can also deduce the GJT elasticity, given the definition of GJT above, as:

GJT elasticity = IVT elasticity + Wait Time elasticity + Walk Time elasticity (5)

6.2. Scope

Evidence on GC/GT elasticities, walk time elasticities, wait time elasticities and headway elasticities were not included in the remit of this study.

Bus GJT elasticities were stated to be within scope. Through our search process, we did not uncover any new directly estimated evidence on bus GJT elasticities. Nor did we uncover any new British evidence on IVT elasticities.

6.3. Current official guidance

While the Department for Transport's current recommendations on bus-fare elasticities are set out, as stated in Section 3.1, in Section 6.4.24 of WebTAG unit M2 (DfT 2017), WebTAG does not address time-based elasticities for bus travel.

What seems to be official thinking with regard to the GJT elasticity is provided in DfT (2017). It is stated that:

> *A national estimate of generalised journey time elasticity of –0.58 has also been used in the calculations.*

Footnote 1 on page 24 states:

> *The GJT elasticity is assumed to be the same as the in-journey time elasticity from TRL (2004) 'The Demand for Public Transport: A Practical Guide'. This is due to a lack of a specific elasticity for GJT and is consistent with the approach taken in the National Bus Model.*

While this recent statement acknowledges that there is little evidence on time elasticities for bus, it will be apparent from the preceding discussion of elasticities in Section 4.1 that the IVT elasticity must be less than the GJT elasticity.

Our interpretation of the TRL (2004) evidence upon which the guidance is based is that the elasticity figure of –0.58 is actually an IVT elasticity. The document does not discuss the concept of GJT in the context of bus elasticities. Taking the figure to reflect the IVT elasticity, we cannot determine how it is arrived at. The only such figure in TRL (2004) is in Section 7.5.1 where the Victoria Transport Policy Institute is cited as reporting an IVT elasticity of –0.58 based on what seems to be American evidence relating to the 1990s.

Our understanding is that it is not made explicitly clear whether the IVT elasticity is short term or long term. We take it to be long term.

6.4. Evolution of conventional wisdom

Unlike bus-fare elasticities, and indeed the wide range of elasticities for rail that are contained in the Passenger Demand Forecasting Handbook (PDFH), there really is no conventional wisdom in this area for bus. This is reflected in the absence of any recommendations on bus time elasticities in WebTAG.

This is presumably partly due to the lack of evidence and partly due to the lack of any need to use evidence. Both of these relate to the fact that bus journey times have historically exhibited little variation, other than trend increases due to congestion, and walk times have not varied materially given largely fixed networks.

In addition, matters such as service frequency, routing and journey times have largely been taken to be the responsibility of bus operators, and hence have not required official recommendations, whereas fares tend to be more policy relevant (as well as easier to estimate their elasticity).

An exception here though is that econometric analysis of bus demand has tended to include some measure of frequency, such as vehicle kilometres operated, probably because it is varied by operators and hence has to be included in models in order to explain demand. However, frequency elasticities were not the subject of this study.

There is very little evidence on GJT elasticities in the bus market. Indeed, this also applies to GT and GC elasticities. So there is reliance on deducing GJT elasticities using the formulae in Section 4.1. While there is some evidence on bus IVT elasticities, deducing it from other evidence remains an attraction. For example, in recognition of the lack of IVT evidence the TRL (2004) document, which underpins the recommendations in Section 4.3, deduced IVT elasticities from fare elasticities alongside values of time and mean levels of fare and IVT.

6.5. The key evidence

As will be clear from the preceding discussion, there is relatively little evidence on bus IVT or GJT elasticities, and some of it is quite dated. The two key pieces of work as far as bus demand is concerned are the TRL (2004) Demand for Public Transport update, whose evidence forms the basis of the Department's recommendations, and the review and meta-analysis of Wardman (2012), part funded by the DfT, which is the most extensive such piece of work in the area. Both of these are described below.

6.5.1. Demand for Public Transport update (TRL 2004)

This study covered both UK and international evidence of which it was aware. It reviews IVT elasticity evidence for bus but the GJT elasticity evidence quite clearly covers only rail in the UK.

As far as bus IVT is concerned, it covers one American study with an IVT elasticity of –0.58 for urban bus, and UK bus priority studies as a whole where the IVT elasticity is stated to be –0.4 but with considerable variation and uncertainty. Evidence for Paris is covered but it covers public transport generically and for door-to-door travel time. The values split by journey purpose range from –0.24 to –0.86 with most in the range –0.5 to –0.75.

The study also used equation (4) to deduce IVT elasticities from bus-fare elasticities given national averages for fares and journey times. It uses a fare elasticity of –0.43, which from the evidence it has reviewed is short run, whereupon the implied journey-time elasticities are also short run.

These implied bus IVT elasticities were –0.43 for commuting, –0.38 for leisure and –1.01 for business, based on national averages for fare and journey time.

The study also identified some 'rare' evidence on GC elasticities for bus travel. Halcrow Fox et al. (1993) reported GC elasticities for 'medium' income levels in the range –0.5 to –0.7 for commuting, –1.4 to –1.6 for leisure, and –0.6 to –0.8 for business, with slight variations for 'low' and 'high' income levels.

On the basis of this evidence, TRL (2004) conclude that, 'With respect to in-vehicle time, evidence on elasticities is limited, particularly for bus. This may reflect that bus speeds are often beyond the control of operators, being largely determined by traffic conditions. Our best estimates are that a representative in-vehicle time elasticity for local bus might be in the range of –0.4 to –0.6.'

There is some uncertainty however as to whether these elasticities are short run, long run, or of some indeterminate nature.

6.5.2. Wardman (2012) review and meta-analysis

This is the most extensive review of time elasticities ever conducted, but as we shall see the amount of bus evidence is limited. The review covered 69 studies between 1977 and 2010 that yielded 427 elasticities relating to GJT, IVT and headway[42]. The modes covered were car, rail and bus.

As far as bus travel was concerned, no evidence relating to GJT elasticities was uncovered. There were only 16 observations of IVT and 16 of headway elasticities. The mean IVT elasticity was –0.63, with a

[42] Headway is the time interval between bus services.

standard error of 0.16, and the mean headway elasticity was –0.29 with a standard error of 0.05. These mean values do not distinguish between short- and long-run effects.

A meta-model was estimated to the elasticities covering all modes and GJT, IVT and headway. It found elasticities to vary by variable, mode, long run and short run, type of data used to estimate the elasticity, distance and purpose.

This model can be used to provide a range of estimated IVT elasticities. This assumes that the relationship, say, between short- and long-run elasticities, or the impact of journey purpose that is discerned in the model and which is common to all modes and each variable, also applies in the specific case of the bus IVT elasticity.[43]

The model implies a short-run (four weekly) bus IVT elasticity of –0.16, with the long-run elasticity implied to be –0.57. The corresponding figures for the headway elasticity were–0.07 and –0.24.

There is support for a long-run leisure IVT elasticity of –0.55 and a long-run commuting IVT elasticity of –0.65.

There was a distance effect apparent in the model but as far as bus is concerned this would relate to longer distance coach services rather than urban bus services.

6.6. Recommended IVT elasticities

In summary, we make the following points:

- DfT guidance recommends a value of –0.58, although admittedly without being explicit on whether it is a short-run or long-run value
- The Wardman (2012) meta-analysis provides a long run value of –0.57
- The Department's recommendations are not directly based on the Wardman (2012) evidence
- We are unaware of more recent evidence in this area.

We would therefore recommend a long-run bus IVT elasticity of –0.60 given little difference between the leisure elasticity of –0.55 and the commuting elasticity of –0.65 from the Wardman (2012) meta-model. We would also point out that this makes sense relative to the bus-fare elasticities; we would expect bus passengers to be more sensitive to fare changes than to journey time variations.

6.7. Deducing GJT elasticities

We are unaware of any directly estimated GJT elasticities for bus. Hence we are in the position of having to deduce them.

Given the dearth of GC elasticity evidence for bus, and that the evidence that exists is rather dated, we have to rule out deducing the GJT elasticity from the GC elasticity.

[43] Some variables have different impacts by mode and variable, such as distance.

We can deduce the GJT elasticity from the fare elasticity using equation (3). This has the attraction of being based upon the bus-fare elasticity, where there is much more evidence. However, our experience of this approach has not been good, with the method open to producing implausibly large GJT elasticities, sometimes in excess of what might be considered a reasonable GC elasticity. Moreover, the implied GJT elasticity can vary considerably across contexts and uncomfortably against other key elasticities that are constant.

Our preference is therefore to recommend that GJT elasticity be calculated as the sum of the IVT elasticity, the walk-time elasticity and the wait-time elasticity.

There is evidence for a long-run IVT elasticity of around –0.60. There is no evidence on variations with distance within the urban context although slight variation would be justified.

The evidence points to a headway elasticity of around –0.25. This can be taken as a reasonable approximation for the wait-time elasticity.[44]

While we are not aware of evidence on walk time, given similar levels of walk time to wait time and similar valuations of the two attributes, it would seem reasonable to use the same elasticity for walk time.

Although walk and wait time are more highly valued than in-vehicle time, their elasticities might be lower because a given proportionate change implies smaller absolute changes in walk and wait time than in IVT.

We can then deduce the headway elasticity from the IVT elasticity as:

$$\text{Headway elasticity} = \text{IVT elasticity} * (w_H * \text{Headway} / \text{IVT})$$

where w_H is the weight attached to headway. This is useful for assessing the consistency of IVT and headway elasticities above. The Abrantes & Wardman (2011) review indicates that a minute of headway is valued at half that of IVT so that w_H=0.5. So for a headway of every 15 minutes, an IVT of 15 minutes and an IVT elasticity of –0.6, the implied headway elasticity is –0.3. In fact, given headway is generally going to be less than twice IVT, the headway elasticity will be less than the IVT elasticity. It seems reasonable to conclude that the headway elasticity here used is consistent with the IVT elasticity used.

The GJT elasticity could then be constructed as the sum of the IVT, walk and wait time elasticities. The headway elasticity proxies for wait time and is taken to be –0.25 and the same value is used for walk time.

The GJT elasticity would then be –1.1.

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[44] The wait-time elasticity is the headway elasticity divided by the elasticity of wait time to headway levels. With random arrivals and wait-time half-service headway, the latter elasticity would be one and the wait-time elasticity would equal the headway elasticity.

6.8. Conclusions

It is clear that there is far less evidence relating to bus-time elasticities than to bus-fare elasticities. This is partly because bus journey times are somewhat less variable than fares. It is also clear that the evidence is dated.

The current recommendation is based on TRL (2004). The shortcomings of this evidence are:

- It is based on a small amount of evidence largely from the 1990s
- Time elasticities in the bus market may have changed since they were originally estimated
- There is some uncertainty as to whether the elasticity is short run, long run or is essentially indeterminate.

Nonetheless, the recommendation corresponds very closely with the bus IVT elasticity implied by the meta-model in Wardman (2012). The latter contains the most extensive review of UK time-based elasticities, although admittedly the evidence base is small. Hence the evidence seems to be pointing to an IVT elasticity of around –0.6. This seems credible, given that we would expect bus passengers to be less sensitive to time variations than to fare variations. The IVT elasticity was also found to be slightly larger for commuting.

Recommended values for the bus GJT elasticity derived using the method provided in this chapter are shown in Table 38 below.

Table 38: Recommended GJT bus elasticities derived from IVT elasticities

	GJT bus elasticity
Overall	-1.1
Commute	-1.15
Leisure	-1.05

There is undoubtedly a dearth of up-to-date evidence in this area, with little or no distinction by key factors such as journey purpose or area type. Should variations in bus IVT and more generally bus GJT be high on the policy agenda, for some time into the future, then there is clearly a need for fresh primary research in this area.

7. Conclusions and recommendations

Below we set out our key conclusions from the research, followed by our recommended bus elasticities and diversion factors. We conclude by identifying important research gaps.

7.1. Key conclusions from the review

Below we set out key conclusions from the review.

We can be confident that we have uncovered much of the relevant literature evidence

In this study we used a two-pronged literature search methodology, incorporating a systematic search of potential literature produced internationally, complemented by a more informal approach involving contacting approximately 100 contacts in academia, industry and other stakeholders to ensure that we identified all relevant research. We also had access to a database being developed in the 'crossmodal' project in Norway, which itself incorporates a literature review and meta-analysis of international evidence on cross-elasticities and diversion factors.

The systematic search component was run in three large literature databases: Transport Research International Documentation (TRID) database, Scopus and Web of Science. It generated over 4,500 references on bus elasticities and 4,500 references on diversion factors, since 2002. These were screened using titles and abstracts by an experienced transport economist to identify 370 potentially relevant references. A similar approach was used to screen literature obtained from contacts. The resulting longlist was then screened a second time, in conjunction with senior project team members and the DfT, to determine the list of 79 papers for review. Given the large number of papers to review and issues of transferability, studies outside of the UK, Europe, the USA and Australia, Canada or New Zealand were excluded at this stage.

While the literature search methodology was very thorough, there is a risk of missing some literature because elasticities and diversion factors may not have been the main subject of the papers searched and therefore may not appear in the title, abstract or keywords. To overcome this risk, our search strategy was specifically broad, generating a large number of potential papers for review and minimising the risk of omitting relevant literature. The team also incorporated a number of academic experts working in this area to ensure that the search strategy picked up key known papers, and we pilot-tested the search terms to test their efficacy in identifying papers known to the review team. We therefore assess the risk of missing key literature sources as low.

We have identified and collated a substantial database on diversion factors, but the evidence is very diverse

The evidence on diversion factors assembled from the literature review, although considerable, is also diverse. In the studies reviewed, data have been collected on diversion rates across a large number of modes, but these are not consistently defined across studies, nor is the choice set of options considered consistent across studies.

Further, the data are collected by different research methods and the intervention that gives rise to a diversion between modes varies between studies. We restrict evidence to studies that reported observed changes, those that reported best alternative to main mode collected in surveys, those collecting transfer time and transfer price information and those collecting stated intentions data. Most surveys reporting observed changes record the impact of an intervention on a particular mode, by asking users of that mode for the mode they previously used. An intervention in this case could be new infrastructure or an improvement to an existing service. These surveys thus record the shift from other modes and the new traffic generated by an intervention. Of course, you would expect different interventions to result in different diversion factors, and this is not taken into account in the analysis. The reported best alternative method, on the other hand, is not associated with a particular intervention, but asks users of an existing mode what they would do if they could no longer travel by that mode. Hence, this method records the **potential** shift away from a given mode to other modes, including not travelling or changing destination. The transfer price and transfer time method operates on a similar principle, by determining the price or journey time at which a user would switch away from a given mode. The dataset also contains a small number of stated intention responses for the closure of existing infrastructure, which is effectively equivalent to reported best alternative.

In addition to diversion factors being distinguished by area or journey type, in some studies they are segmented by trip purpose or by user type.

In total 934 diversion factors were obtained from the literature for ten aggregated modes. It is noted that one paper could generate multiple diversion factors. While this is a sizeable amount of data, it is not very large when considering the aim of identifying diversion factors between pairs of modes, including from and to bus, rail, car, light rail/metro, walking and cycling, and taking account of geographical area and passenger type (full-paying and concessionary travellers).

The literature review includes studies from Europe, USA and Canada, Australia and New Zealand as well as the UK. Although most of the data is from the UK (803 of the 934 diversion factors), including data from other countries has been useful for modes where data is sparse. This is particularly the case for cycle where more than half of the data on diversion from this mode and a quarter of data on diversion to this mode comes from outside the UK.

Most diversion factor data are available for bus, rail and car. Over half of the data is for urban areas: about a third for intercity areas (about a tenth is not defined). In the urban areas, nearly 90% of the data is for metropolitan areas with 5% for metropoles and urban-conurbations. There is little data for small towns or rural areas. Only 13 diversion factor values were for concessionary travellers.

Very little new evidence on bus fare elasticities has been uncovered in the evidence review

WebTAG guidance on bus-fare elasticities is based on the work of Dargay & Hanly (1999). Specifically, it states:

'Elasticities of bus trips with respect to bus fares for full fare paying passengers have been found to lie typically in the range –0.7 to –0.9 for changes over a period longer than 5 years (Dargay and Hanly). Unless analysts can provide a good reason otherwise, the Department's view is that the annual average bus fare elasticity from the base year model should lie within this range. It should be noted that up to a third of bus trips made in the off-peak and some in the morning peak are made by concessionary passengers free of charge. Their demand will be unaffected by changes in fares. If possible, it would be useful to estimate the fare elasticity for full fare paying passengers separately noting that there are several half-fare or similar schemes for children and students. Including concessionary passengers would tend to reduce the elasticities given above to around –0.4 with a lower elasticity in the off-peak.'

Our literature search did not identify much new British evidence on bus-fare elasticities, with the most recent work in this area being undertaken in the Toner et al. (2010) study. It is interesting that the Toner et al. (2010) recommendations for short-run fare elasticities for the full-fare market are very much in line with the equivalent Dargay & Hanly (1999) recommendations, thereby supporting official guidance. The major review study of Wardman (2014) also finds the bus-fare elasticities to be in line with these two studies and official guidance.

Similarly, we have uncovered very little new evidence on bus journey time elasticities

We find that there is very little evidence on bus in-vehicle time (IVT) or generalised journey time (GJT) elasticities, and some of it is quite dated. The two key pieces of work undertaken in the period of review looking at bus journey-time elasticities is TRL (2004) Demand for Public Transport update, whose evidence forms the basis of the Department's recommendations, and the review and meta-analysis of Wardman (2012), part-funded by the DfT, which is the most extensive such piece of work in the area.

As we understand, the TRL (2004) review study includes one American study with an IVT elasticity of –0.58 for urban bus and UK bus priority studies as a whole where the IVT elasticity is stated to be –0.4, but with considerable variation and uncertainty. The study also deduces IVT elasticities from bus-fare elasticities, given national averages for fares and journey times. The calculated implied bus IVT elasticities were –0.43 for commuting, –0.38 for leisure and –1.01 for business, based on national averages for fare and journey time. TRL (2004) estimate that a representative in-vehicle time elasticity for local bus might be in the range of –0.4 to –0.6.

Wardman (2012) undertakes the most extensive review of time elasticities ever conducted, covering 69 studies between 1977 and 2010 that yielded 427 elasticities relating to GJT, IVT and headway. The modes covered were car, rail and bus. However, even in that data set, bus evidence is limited. No evidence relating to bus GJT elasticities was uncovered. There were only 16 observations of IVT and 16 of headway elasticities. The mean IVT elasticity was –0.63, with a standard error of 0.16, and the mean headway elasticity was –0.29 with a standard error of 0.05. These mean values do not distinguish between short- and long-run effects. A meta-model was estimated to the elasticities covering all modes and GJT, IVT and headway. It found elasticities to vary by variable, mode, long run and short run, type of data used to estimate the elasticity, distance and purpose. The model implies a short-run (four weekly) bus

IVT elasticity of –0.16, with the long-run elasticity implied to be –0.57. The corresponding figures for the headway elasticity were –0.07 and –0.24. There is support for a leisure IVT elasticity of –0.55 and a commuting IVT elasticity of –0.65. A method is provided to deduce GJT elasticities from the IVT elasticities.

7.2. Recommendations

Below we set out recommendations for the three areas of interest.

7.2.1. Diversion factors

Below we set out recommended diversion factors, for bus as the intervention mode. Corresponding tables for interventions on other modes can be found in Chapter 4. We also present recommended ranges of diversion factors for the five intervention modes for which data are available: bus, car, rail, light rail/metro and cycle. We set out ranges to reflect the uncertainty in the data. These ranges can be used together with the more detailed tables in the report to determine the most appropriate set of values for a given application. Values currently used based on the White Book are derived from a small number of studies. They mainly fall within the recommended ranges, or the differences can be explained by the data sources and choice sets used.

Table 39: Recommended diversion factor values for an intervention on bus

Recipient/source mode	National weighted mean	Metropolitan[1]	Metropolitan (no light rail)	Metropolitan commute	Urban-conurbation[2]
car	0.24	0.25	0.30	0.30	0.29
rail	0.11	0.11	0.14	0.07	0.10
light rail	0.16	0.18		0.25	
cycle	0.04	0.06	0.07	0.07	0.04
walk	0.14	0.18	0.22	0.14	0.26
taxi	0.12	0.10	0.12	0.07	0.13
no travel	0.19	0.12	0.15	0.10	0.17
N[3]		94	86	19	25

Source: New analysis. [1] Data for metropoles are combined with metropolitan. [2] There are no light rail data for urban conurbations. [3] N denotes the number of data points used to calculate the average.

Table 40: Recommended diversion factors for interventions on bus, car, rail, light rail/metro and cycle

Intervention mode	Recipient/source mode						
	Bus	Car	Rail	Light rail / metro	Cycle	Walk	Generated traffic (no travel)
Bus		All trip purposes: 0.20-0.35 Commute: 0.30-0.55	Urban areas: 0.05-0.2 Intercity: 0.45-0.65	Urban areas: 0.05-0.35	Urban areas: 0.04-0.08	Urban areas: 0.1-0.3	Urban areas: 0.10-0.20 Interurban: 0.07-0.11
Car	Urban areas: 0.20-0.40 Interurban: 0.07-0.11		Urban areas: 0.05-0.20 Interurban: 0.55-0.75	Urban areas: 0.10-0.35	Urban areas: <0.1	Urban areas: 0.05-0.15	Urban areas: 0.1-0.25 Interurban: 0.10 - 0.25
Rail	Urban areas: 0.25-0.4 Interurban: 0.1-0.2	Urban areas: 0.3-0.45 Interurban: 0.4-0.55		Urban areas: 0.05-0.15	Urban areas: <0.1	Urban areas: <0.05	Urban areas: 0.10-0.20 Interurban: 0.10-0.20
Light rail/ metro	Urban areas: 0.25-0.4	Urban areas: 0.15-0.3	Urban areas: 0.15-0.3		Urban areas: < 0.1	Urban areas: < 0.05	Urban areas: 0.10-0.20
Cycle	0.150.05-0.4, higher for walk and bus						

7.2.2. Bus fare elasticities

As part of this study, our literature search and requests from key academics, operators and authorities have not yielded anything more recent than the Toner et al. (2010) study. Current WebTAG guidance is based on earlier work (Dargay & Hanly, 1999). Nonetheless, the Toner et al. (2010) recommendations for short-run fare elasticities for the full-fare market are very much in line with the equivalent Dargay & Hanly (1999) recommendations, thereby supporting official guidance. The major review study of Wardman (2014) also finds the bus-fare elasticities to be in line with these two studies and official guidance.

While the literature evidence suggests no real change in bus-fare elasticities, we discuss reasons why further work should be undertaken in this area below.

7.2.3. Bus journey time elasticities

It is clear that there is far less evidence relating to bus-time elasticities than to bus-fare elasticities. This is partly because bus journey times are somewhat less variable than fares. It is also clear that the evidence is dated.

The current recommendation is based on TRL (2004). The shortcomings of this evidence are:

- It is based on a small amount of evidence largely from the 1990s
- It is not inconceivable that time elasticities in the bus market have changed since they were originally estimated
- There is some uncertainty as to whether the elasticity is short run, long run or is essentially indeterminate.

Nonetheless, the recommendation corresponds very closely with the bus IVT elasticity implied by the meta-model in Wardman (2012). The latter contains the most extensive review of UK time-based elasticities, although admittedly the evidence base is small.

Hence the evidence seems to be pointing to an IVT elasticity of around –0.6. This seems credible, given that we would expect bus passengers to be less sensitive to time variations than to fare variations.

We also provide a means for deriving a GJT elasticity for bus from IVT elasticities, which we recommend to be –1.1, although this contains a number of assumptions regarding walk- and wait-time elasticities.

7.3. Evidence gaps

This review has identified a number of gaps in evidence around bus elasticities and diversion factors.

More and better evidence on diversion factors should be collected

In order to be able to explore the wide range of diversion factors desired – by the mode from which traffic would come from, the mode it would be diverted to and by geographical area – a large evidence base is required. In particular, most studies included in the dataset cover metropolitan areas and more data are needed on diversion factors for journeys in urban conurbations, small towns and rural areas. Moreover, to understand better the influence of other explanatory factors, such as the type of intervention or the impact of the research methodology, even more data are required. We also note that the set of travel alternatives on which the diversion is based also has an impact on the diversion factor. Again, this is difficult to isolate without more data. Moreover, diversion factors are not symmetric and can only be determined for interventions on modes for which reported data are available. We have presented diversion factors for bus, car, rail, light rail and cycle but the data on cycle interventions is limited and there are no data on interventions aimed at pedestrians.

While we have restricted ourselves to studies based on observed data, we have included transfer price and transfer time, or stated best alternative from surveys to provide evidence on actual behaviour (modelling and stated preference studies were excluded). While in general we do not see substantial differences in the diversion-factor values across these sources, it would be better to focus on estimates of diversions from real transport changes. Efforts should be made to collect such evidence when evaluating impacts from transport interventions. These data could be compiled, over time, to complement the work that has been done in this study.

The evidence base on bus fare elasticities is dated

While there is a consistency in the empirical evidence concerning the fare elasticity in the full-fare market, which is of primary interest, we have to recognise that this evidence is dated and much has happened in the bus market and its broader environment more recently. We also have to recognise that the evidence base is not as robust as we might like because of the difficulties involved in disentangling the concessionary market.

It is therefore timely to revisit the demand for bus travel and its fare elasticity since the last major study in 2010. The estimation needs to focus on the full-fare market; the presence now of a sufficiently long time series where concessionary travel has been free does not help matters. Possible ways forward are:

- Obtain data that separately identifies full fare, child and senior concessionary travel so that fare elasticities can be estimated in the two markets where fares are paid. Our understanding is that STATS100 data does not permit this, so other data should ideally be sourced.
- Analyse STATS100 data for the whole market, and either use the decompositional method of Toner et al. (2010) or assume that the proportion of the market made up by concessions will remain constant over time, and hence use the whole-market elasticity going forward.
- Obtain fare indices to complement the STATS100 revenue data and model revenue – which does not contain concessionary travel – as a function of the full-fare index. The resulting full-fare revenue elasticity can be converted to a fare elasticity by subtracting one.

In all this, it is worth remembering, as previous studies have shown, that the bus-fare elasticity is not a single number. There should be appropriate consideration of elasticity variations according to the fare charged, local market conditions, area type and other factors that can be investigated that might impact on bus fare elasticities.

There is very little evidence on bus journey time elasticities

There is undoubtedly a dearth of up-to-date evidence in this area, with little or no distinction by key factors such as journey purpose or type of area. Should variations in bus IVT and more generally bus GJT be high on the policy agenda, for some time into the future, then there is clearly a need for fresh primary research in this area.

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Annex A. Search protocol for bus elasticities and diversion factors

Background

The central aims of this study are to:

- Review and synthesise evidence on bus elasticities and a range of diversion factors;
- Identify a preferred set of parameters, with clear justification and consideration of quality variations, and provide recommendations for possible inclusion in WebTAG as official guidance.

Demand elasticities denote the sensitivity of bus patronage to changes in relevant variables; here fare and generalised journey time. Diversion factors are important in determining the source and extent of new traffic. For example, if a rail intervention results in increased demand, the diversion factor for bus tells us what proportion of that demand has come from bus.

Although we are predominantly interested in the diversion of traffic from other modes to bus and vice versa, we need to consider all pair-wise effects (car-rail, bike-walk etc) for completeness.

Table 41: Elasticities and factors to be updated (from the ITT)

Technical values	Breakdowns	Current sources
Commercial market fare elasticities for buses	Overall, by area[1], by short-run / long-run, by distance travelled	TRL (2004)
GJT elasticities for buses	Overall, by short-run / long-run	TRL (2004)
GJT elasticities for buses	By area, by distance travelled	New values of interest
Diversion factors for buses	Overall, by area, by passenger type (fare paying and concessionary)	TRL (2004)
Diversion factors for rail	Overall, by PDFH[2] flow categories	WebTAG Unit A5.4 (DfT 2015)
Diversion factors for cars	Overall, by area	TRL (2004)
Diversion factors for metro/light rail	Overall, by area	New values of interest
Diversion factors for walking	Overall, by area	New values of interest
Diversion factors for cycling	Overall, by area	New values

General inclusions and exclusions

Criteria	Include
General	
Published in or after 2003 (1990)	✓
English language, UK focus, comparison study with UK or study of OECD/EU countries	✓
Type of publication/study	
Conference abstract/paper	✓
Journal article – systematic reviews, REAs, quantitative, high quality observational and qualitative studies	✓
High quality agency reports (e.g. OECD, DfT, EU)	✓
PhD theses	✓
Scope	
Contains technical values sought in scope of work (disaggregated by area, distance, short run, long run etc)	✓
Contains other data (e.g. cross-price elasticities) that can be used to determine technical values, e.g. diversion factors	X
Information relevant for assessing quality of technical values	✓
Modelling or SP studies	X[1]
Main travel model only, except for walk and cycle which may be access/egress modes	✓

[1] Unless insufficient studies using observations.

<u>Publication date:</u> As can be seen from Table 41, many of the values to be updated were published in the TRL (2004) report. The expectation is that data published before 2003 would be captured in this 2004 study. Hence in the review we will exhaustively screen papers published in or after 2003. A more selective search of papers from 1990 to 2002 will also be undertaken.

<u>Technical values:</u> Cross elasticities are not part of the study remit. Papers that cover cross elasticities in addition to diversion factors and/or bus-fare and journey-time elasticities are retained.

<u>Study types:</u> As noted in the tender documents, the preference is for technical values based on empirical data. References that are model- or Stated Preference (SP)-based are captured in the screening and are therefore available as a secondary source of data, if required. They will not be included in the initial longlist.

Databases

Based partly on our experience from previous literature reviews in this study we will use the following databases: TRID, Web of Science, Scopus, Phd Dissertation database.

Proposed search strategies

Elasticities and diversion factors may not be the main purpose of the papers searched and may not appear in the title, abstract or keywords. The search strategies try to take account of this.

1) Bus fare and generalised journey time elasticities

Search aim	Explicit Conditions (general exclusions above)	Search terms (OR between terms in cells, AND between columns)	
Bus elasticities	TRID subjects: passenger transportation, public transportation, economics Web of Science filters: Transportation (Research Area) and Transportation Science & Technology (Web of Science Categories)	Bus, public transit, public transport*, coach, transit demand	Elastic*, sensitiv*, fare(s), generalised price, generalised cost, journey time, service level, demand response, ticket price, ticket cost
	TRID: public transportation	Travel demand, transport demand, demand model, travel choice, demand for travel	Elastic*, sensitiv*, fare(s), generalised price, generalised cost, journey time, ticket price, ticket cost, service level, subsid*

(*represents truncation, where supported by databases)

It is assumed all databases will be searched, with limiting criteria on some as specified in the table above.

These searches may also generate articles relevant for diversion factors. Some of the papers below look at own-price demand elasticities and diversion parameters but this is not obvious from the title, keywords and abstract.

2) Diversion factors

As noted above, some of these will be picked up by the bus elasticity searches.

The searches have been divided into motorised and non-motorised (although a paper found under the motorised search may clearly contain non-motorised modes and vice-versa). The terms are designed to find papers looking at diversion effects.

Search aim	Explicit Conditions (general exclusions above)	Search terms (OR between terms in cells, AND between columns)	
Diversion factors (motorised)	TRID subjects: passenger transportation, public transportation, economics Web of Science	Bus, public transit, public transport*,coach, car, auto*, private transport, transit. Rail, light rail, metro, road users, taxi	Diversion parameter, diversion factor, diversion ratio, transfer factor, transfer parameter, demand interaction, transfer elasticity, mod* shift, mod* choice, best alternative, alternative mode, displace*, new journey(s), new traffic
Diversion factor (non-motorised)		Cycl*, walk*, pedestrian, bike, bicycle	As above

Including cycl* and displace* in the searches caused the searches to crash as too many citations were included. An additional search will now be run as follows:

Search aim	Explicit Conditions (general exclusions above)	Search terms (OR between terms in cells, AND between columns)	
Diversion factor (non-motorised)		cycleway, 'cycle route', 'cycling route'	Diversion parameter, diversion factor, diversion ratio, transfer factor, transfer parameter, demand interaction, transfer elasticity, mod* shift, mod* choice, best alternative, alternative mode, new journey(s), new traffic

The results of this search are not included in the current longlist.

The searches were piloted on the following references.

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Data extraction and coding

Extracted Data	Permitted values	Extracted Data	Permitted values
Study Number		Intervention mode	1 = bus
Subnumber			2 = car
Authors			3 = car driver
Title			4 = car passenger/lift
Publication Date			5 = cycle
Source	1 = journal/book		6 = walk
	2 = conference paper		7 = rail
	3 = published report		8 = light rail (tram)
	4 = unpublished report		9 = taxi
	5 = working paper		10 = metro
	6 = thesis		11 = don't travel
	7 = other		12 = change destination
External Peer Review	1 = yes		13 = change time of day
	2 = no		14 = BRT
	3 = not clear		15 = air
Country/Location of study	1 = UK		16 = other bus
	2 = Northern Europe		17 = other station
	3 = Other Europe		18 = other (mode not specified)
	4 = USA		19 = Public transport
	5 = Australia/NZ/Canada		20 = walk/cycle
	6 = Rest of World		21 = bike hire/share
City/Region			22 = HSR
Research Method	1 = observed change		23 = car share
	2 = reported best alternative	Recipient/source mode	As per intervention mode
	3 = stated intention	Choice set	Combinations of modes above
	4 = transfer price	Trip purpose	1 = commute
	5 = transfer time		2 = business
Intervention	1 = new infrastructure		3 = personal business
	2 = improvement/ deterioration		4 = leisure
	3 = policy/regulatory change		5 = shopping
	4 = package of measures		6 = education
Sample size			7 = VFR
Years of data collection			8 = holidays/short break
Journey type	1 = urban		9 = non-commute
	2 = interurban		10 - no distinction (all)
	3 = all (no distinction)		11 = non business
Area type	1 = large metropolis		12 = access intercity station
	2 = metropolitan		13 = other
	3 = urban conurbation	Diversion factor	
	4 = small towns	Diversion segmentation	1 = headline
	5 = rural		2 = segmentation
	6 = no distinction	Demand	1 = number of trips
Passenger type	1 = fare paying		2 = Mileage
	2 = concessionary traveller	Segmentation:	Yes/no
	3 = multiple car occupancy	Time of day	
	4 = all/no distinction	Age	
Attribute	1 = monetary cost/price	Income	
	2 = journey time	Gender	
	3 = new infrastructure	Car availability	
Description of intervention/attributes		Trip length	
		Segmentation description	
		Comments	

Annex B. Additional analysis

In this appendix we provide additional analysis of the diversion factors.

Additional bus diversion factor results

Table 42: Average diversion factors for bus as intervention mode, by journey purpose

Recipient/source mode	Mean diversion factor	N	Standard error
Commute			
Car	0.44	13	0.06
Rail	0.35	5	0.17
Light rail/metro	0.29	2	0.24
Cycle	0.08	2	0.01
Walk	0.16	3	0.09
Taxi	0.08	2	0.06
No travel	0.14	7	0.07
Other	0.12	12	0.03
Leisure			
Car	0.26	7	0.05
Rail	0.38	7	0.09
Light rail/metro	0.58	1	
Cycle	0.02	1	
Walk	0.52	1	
Taxi	0.10	1	
Air	0.04	3	0.02
No travel	0.13	8	0.03
No distinction[1]			
Car	0.23	25	0.03
Rail	0.09	4	0.02
Light rail/metro	0.08	4	0.02
Cycle	0.04	5	0.01
Walk	0.15	6	0.06
Taxi	0.14	4	0.04
No travel	0.18	9	0.03
Other	0.07	6	0.02

1. These values are from studies that do not distinguish trip purpose only. Aggregate values that also include data from studies with journey purpose segmentation are presented in Table 16.

Table 43: Average diversion factors from bus, by research methodology

Diversion to	Mean diversion factor	N	Standard error
All data			
Car	0.29	63	0.02
Rail	0.36	33	0.04
Light rail/metro	0.19	8	0.08
Cycle	0.06	13	0.01
Walk	0.21	13	0.05
Taxi	0.12	10	0.02
Air	0.08	9	0.02
No travel	0.14	44	0.02
Other	0.07	37	0.01
Behaviour – observed change			
Car	0.30	30	0.04
Cycle	0.02	1	
Walk	0.15	3	0.14
No travel	0.31	5	0.05
Other	0.15	10	0.02
Behaviour - best alternative and transfer method combined			
Car	0.29	33	0.03
Rail	0.36	33	0.04
Light rail/metro	0.19	8	0.08
Cycle	0.07	12	0.01
Walk	0.22	10	0.05
Taxi	0.12	10	0.02
Air	0.08	9	0.02
No travel	0.11	38	0.01
Other	0.04	27	0.01

Additional car diversion factor results

Table 44: Average diversion factors from car, by journey purpose

Purpose	Mean diversion factor	N	Standard error
Commute	0.20	32	0.05
Business	0.21	29	0.05
Personal business	0.12	8	0.02
Leisure	0.21	37	0.04
VFR	0.22	18	0.06
Holidays/short break	0.22	18	0.03
No distinction	0.11	19	0.02
Total	0.19	161	0.02

Table 45: Average diversion factors from car, by research methodology

Diversion to	Mean diversion factor	N	Standard error
All data			
Bus	0.18	34	0.03
Rail	0.45	32	0.05
Light rail/metro	0.23	8	0.06
Cycle	0.05	7	0.02
Walk	0.09	7	0.02
Taxi	0.08	7	0.03
Air	0.07	10	0.01
No travel	0.17	31	0.02
Other	0.07	26	0.01
Behaviour – observed change			
Bus	0.15	2	0.13
Rail	0.27	1	
No travel	0.02	1	
Other	0.01	1	
Behaviour – other			
Bus	0.18	32	0.03
Rail	0.46	31	0.06
Light rail/metro	0.23	8	0.06
Cycle	0.05	7	0.02
Walk	0.09	7	0.02
Taxi	0.08	7	0.03
Air	0.07	10	0.01
No travel	0.17	31	0.02
Other	0.07	25	0.01

Additional rail diversion factor results

Table 46: Average diversion factors from rail, by research methodology

Diversion to	Mean diversion factor	N	Standard error
All data			
Bus	0.22	71	0.02
Car	0.34	94	0.02
Light rail/metro	0.09	15	0.01
Cycle	0.04	14	0.01
Walk	0.01	12	0.01
Taxi	0.04	15	0.01
Air	0.29	15	0.04
No travel	0.17	65	0.01
Other	0.09	46	0.01
Behaviour – observed change			
Bus	0.25	21	0.04
Car	0.31	22	0.03
Air	0.34	4	0.09
No travel	0.25	23	0.03
Other	0.18	10	0.05
Behaviour – best alternative (plus SI)			
Bus	0.23	27	0.03
Car	0.43	26	0.03
Light rail/metro	0.08	9	0.02
Cycle	0.05	11	0.01
Walk	0.02	9	0.01
Taxi	0.05	12	0.01
No travel	0.16	25	0.02
Other	0.18	19	0.02
Behaviour – transfer method			
Bus	0.18	23	0.03
Car	0.55	23	0.03
Air	0.29	10	0.04
No travel	0.09	23	0.01
Other	0.05	21	0.01

Additional diversion factor results by choice set and by mode diversion is from

Table 47: Average diversion factors from bus, by choice set

		Diversion to									Total (per row - may vary per pair)
	bus	car	rail	light rail/metro	cycle	walk	taxi	air	no travel	other	
1,2		0.15									6
		0.04									
1,2,10		0.56							0.16		16
		0.05							*0.03*		
1,2,9,10		0.36							0.51	0.09	3
1,2,3,4,5,6,7,9,10		0.42	0.08	0.06	0.04	0.10	0.12		0.09	0.07	40
		0.08	*0.02*	*0.01*	*0.01*	*0.02*	*0.02*		*0.02*	*0.02*	
1,2,3,5,6,7,9,10		0.29	0.10		0.05	0.41	0.05		0.04	0.02	21
		0.08	*0.02*		*0.02*	*0.06*	*0.03*		*0.02*	*0.01*	
1,3,4,5,6,7,9,10			0.13	0.11	0.07	0.17	0.23		0.18	0.11	7
1,2,3,5,6,7,9		0.10	0.11		0.05	0.29	0.15		0.17		7
		0.05									
1,2,3,4,9		0.03	0.02	0.55					0.21		8
		0.01	*0.01*	*0.03*					*0.04*		
1,2,3,5,9		0.36	0.37		0.15				0.14		8
		0.01	*0.03*		*0.02*				*0.01*		
1,2,5,6		0.05			0.02	0.01					5
		0.01									
1,2,6,9,10		0.23				0.44			0.27	0.09	4
1,2,3,8,9		0.22	0.59					0.02	0.18		4
1,2,3,8,9,10		0.30	0.45					0.09	0.11	0.05	40
		0.03	*0.04*					*0.02*	*0.02*	*0.01*	
1,2,3,9,10		0.31	0.60						0.06	0.03	40
		0.04	*0.05*						*0.01*	*0.02*	
1,2,9		0.40							0.27		2
1,9									0.21		7
									0.04		

Standard errors are shown in italics in the row below the average.

Table 48: Average diversion factors from car, by choice set

		Diversion to									Total (per row - may vary per pair)
	bus	car	rail	light rail/metro	cycle	walk	taxi	air	no travel	other	
1,2,3,4,5,6,7,9,10	0.22		0.07	0.08	0.08	0.11	0.14		0.19	0.12	32
	0.03		*0.02*	*0.02*	*0.02*	*0.03*	*0.01*		*0.02*	*0.01*	
1,2,3,4,9	0.38		0.03	0.39					0.17		16
	0.06		*0.01*	*0.04*					*0.04*		
1,2,3,5	0.27		0.27								2
1,2,3,5,6,7,9,10	0.47		0.24		0.01	0.06	0.01		0.16	0.05	21
	0.03		*0.04*		*0.00*	*0.01*	*0.01*		*0.08*	*0.02*	
1,2,3,8,9	0.10		0.42					0.01	0.48		8
	0.04		*0.03*					*0.00*	*0.01*		
1,2,3,8,9,10	0.07		0.65					0.09	0.11	0.07	40
	0.01		*0.04*					*0.01*	*0.02*	*0.03*	
1,2,3,9,10	0.11		0.70						0.14	0.06	41
	0.03		*0.06*						*0.03*	*0.02*	
1,2,9,10	0.02								0.02	0.01	3

Standard errors are shown in italics in the row below the average.

Table 49: Average diversion factors from rail, by choice set

	Diversion to										Total (per row - may vary per pair)
	bus	car	rail	light rail/metro	cycle	walk	taxi	air	no travel	other	
1,2,3,4,5,6,7,9,10	0.16	0.55		0.09	0.02	0.01	0.06		0.08	0.04	40
	0.03	*0.07*		*0.01*	*0.00*	*0.00*	*0.01*		*0.02*	*0.01*	
1,2,3,4,9,10	0.19	0.40		0.05					0.18	0.06	15
	0.06	*0.10*		*0.02*					*0.02*	*0.01*	
1,2,3,5,6,7,9,10	0.47	0.43			0.00	0.00	0.00		0.08	0.01	21
	0.06	*0.08*			*0.00*	*0.00*	*0.00*		*0.02*	*0.01*	
1,2,3,5,6,9,10	0.41	0.20			0.07	0.07			0.13	0.13	6
1,2,3,5,7,9	0.47	0.26			0.09		0.05		0.14		10
	0.04	*0.05*			*0.01*		*0.01*		*0.00*		
1,2,3,5,9	0.34	0.36			0.13				0.13		8
	0.00	*0.06*			*0.01*				*0.01*		
1,2,3,6	0.03	0.44				0.01					6
	0.02	*0.13*				*0.00*					
1,2,3,7,9	0.28	0.38					0.02		0.32		16
	0.04	*0.03*					*0.01*		*0.03*		
1,3,4,5,6,7,9,10	0.36			0.17	0.02	0.03	0.14		0.21	0.08	7
1,2,3,8,9	0.21	0.35						0.24	0.19		28
	0.05	*0.07*						*0.07*	*0.04*		
1,2,3,8,9,10	0.08	0.43						0.33	0.10	0.05	40
	0.01	*0.03*						*0.03*	*0.01*	*0.02*	
1,2,3,9	0.19	0.41							0.29		24
	0.05	*0.04*							*0.04*		
1,2,3,9,10	0.24	0.48							0.14	0.12	100
	0.04	*0.05*							*0.02*	*0.02*	
2,3,9		0.50							0.50		2

Standard errors are shown in italics in the row below the average.

Table 50: Average diversion factor from light rail/metro, by choice set

	Diversion to										Total (per row - may vary per pair)
	bus	car	rail	light rail/metro	cycle	walk	taxi	air	no travel	other	
1,2,3,4,5,6,7,9,10	0.23	0.45	0.09		0.04	0.03	0.10		0.07	0.04	40.00
	0.04	*0.06*	*0.01*		*0.01*	*0.01*	*0.01*		*0.01*	*0.00*	
1,2,3,4,5,6,9	0.42	0.12	0.19		0.01	0.01			0.22		6
1,2,3,4,6,7	0.28	0.20	0.43			0.03	0.02				26
	0.02	*0.02*	*0.04*			*0.01*	*0.01*				
1,2,3,4,6,9,10	0.54	0.13	0.06			0.04			0.22	0.01	6
1,2,3,4,9	0.60	0.15	0.04						0.08		8
	0.05	*0.02*	*0.01*						*0.01*		
1,2,3,4,9,10	0.22	0.21	0.27						0.24	0.02	30
	0.01	*0.04*	*0.02*						*0.05*	*0.00*	
1,2,,4,5,9	0.60	0.16			0.11				0.10		8
	0.05	*0.05*			*0.02*				*0.02*		
1,3,4,5,6,7,9,10	0.45		0.14		0.07	0.06	0.21		0.16	0.07	7
2,4,9	0.15								0.28		4
	0.05								*0.02*		

Standard errors are shown in italics in the row below the average

Table 51: Average diversion factors from cycle, by choice set

	Diversion to										Total (per row - may vary per pair)
	bus	car	rail	light rail/metro	cycle	walk	taxi	air	no travel	other	
1,2,3,4,5,6,10	0.13	0.03	0.19	0.16		0.32				0.03	14
	0.08	*0.00*	*0.16*	*0.09*		*0.03*				*0.02*	
1,2,3,5	0.29		0.29								2
1,2,3,5,6	0.26	0.20	0.09			0.46					4
1,2,4,5,6,9,10	0.18	0.07		0.18		0.22			0.24	0.10	6
1,2,5,6	0.37	0.27				0.15					7
	0.15	*0.11*				*0.11*					
1,2,5,6,7		0.16				0.27	0.11				3

Standard errors are shown in italics in the row below the average

Table 52: Average diversion factors from air, by choice set

	Diversion to										Total (per row - may vary per pair)
	bus	car	rail	light rail/metro	cycle	walk	taxi	air	no travel	other	
1,2,3,8,9,10	0.03	0.33	0.51						0.10	0.01	39
	0.02	*0.12*	*0.11*						*0.02*	*0.02*	

Standard deviations are shown in italics in the row below the average