Cycling Diversion Factors

Rapid Evidence Assessment

Summary Report

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Cycling Diversion Factors Rapid Evidence Assessment Summary Report to Department for Transport

Contents

Executive Summary

The report presents findings from a rapid evidence assessment which set out:

1. To identify and evaluate evidence on cycling diversion factors of relevance to the UK context; and
2. To recommend a revised set of cycling diversion factors for inclusion in Transport Appraisal Guidance (TAG).

Cycling diversion factors

Cycling diversion factors represent estimates of the percentage of any *additional* cycling trips which have shifted from other modes, or are trips that were not otherwise made, and which may be associated with investment in cycling (for example, new or enhanced infrastructure or behaviour change measures). These are termed **marginal diversion factors**. Marginal diversion factors may not be the same as average diversion factors, which are the percentage of existing cyclists' who would, if cycling were not available, otherwise travel by other modes.

Cycling diversion factors in TAG

The current cycling diversion factors presented in the TAG databook (table A5.4.7, (DfT, 2022)) are shown in Table 1. The cycling diversion factor of 0.11 for car to cycle (for metropolitan areas with a multi-modal choice set) indicates that for every 100 additional cycle trips generated as result of an intervention, 11 may be assumed to have transferred from car.

Table 1: Current TAG cycling diversion factors

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 (number of studies)	**33**	
Source: DfT (2022) table A5.4.7		

The diversion factors currently presented in TAG were drawn from an earlier rapid evidence assessment reported in Dunkerley et al. (2018) and there are some known limitations of the underpinning evidence base and applicability of the diversion factors, as noted in TAG unit A.5.1 (DfT, 2020). There was sufficient evidence for metropolitan areas, but insufficient evidence to produce different values by trip length or journey purpose. In addition, a number of contributing studies were from the international literature.

Evidence search and selection strategy

The search process combined an online search with direct requests for evidence made by the Department for Transport (DfT) and UWE teams to academics, transport authorities and cycling organisations. The search generated 87 sources which were screened to return 15 UK and five international sources for inclusion in the review. Six international review papers were also evaluated and summarised and these reviews confirmed the finding that there are few published studies reporting direct evidence of marginal cycling diversion factors.

Recommendations on conventional cycle diversion factors

Of the 20 reviewed sources (excluding the international literature reviews), four UK studies were identified as being suitable for providing guidance on typical marginal cycling diversion factors. One study related to infrastructure (Sloman et al. (2021), cycle lane and junction treatments in 7 cities in England). Three studies related to non-infrastructure interventions (Cycling UK (2021), cycle maintenance provision; Murphy and Usher (2015), Dublin cycle hire scheme; and Woodcock et al. (2014), London cycle hire scheme).

The cycle city ambition (CCA) fund evidence reported in Sloman et al. (2021) provided marginal cycling diversion factors estimated from road user intercept surveys (RUIS) conducted at cycling infrastructure schemes implemented across 7 cities in England.

A secondary analysis has been performed on the CCA scheme RUIS data to arrive at a best estimate of typical mean marginal cycling diversion factors (for infrastructure interventions) by calculating a weighted mean across the 7 RUIS surveys (which accounts for sample size and hence uncertainty of the estimate). These estimates are presented in Table 2.

Table 2: Normalised weighted mean marginal cycling diversion factors for infrastructure interventions

Transfer from mode	Weighted mean marginal diversion factor	95% confidence Interval	Normalised marginal diversion factor
Would use car (as driver or pass)	25%	22%-28%	24%
Would use other modes	55%	51%-58%	53%
Would not make this journey	24%	20%-28%	23%
Sum	104%		100%

The normalised estimate of 24% for the car to cycle diversion factor is significantly higher than (more than double) the existing TAG value of 11%. However, it is thought to be a reasonable revised estimate given that: (i) it is based on up to date observational evidence for infrastructure interventions in England; (ii) it is within the range of international evidence for Denmark and USA; and (iii) the confidence intervals for estimates for individual CCA cities, in most cases, intercept with the 24% value.

Incorporating revised diversion factors in TAG

There are two options for including these revised marginal cycling diversion factor estimates in the TAG databook:

1. Entirely replace the existing TAG diversion factors with the revised values presented in Table 2 (column titled "Normalised marginal diversion factors"). This will mean reducing the number of 'transfer from' transport modes available in the diversion factor choice set presented in TAG.
2. Re-normalise the existing TAG diversion factors so that they match the revised normalised values. These values are shown in Table 3 (column titled "TAG Metropolitan re-normalised to match CCA estimates"). This option retains the level of modal disaggregation currently presented in TAG.

A judgement will need to be made as to whether the disaggregation by mode is retained or replaced with a guidance framework, placing a more explicit requirement on analysts to draw on local evidence.

Table 3: TAG diversion factors re-normalised to match weighted mean diversion factors

Recipient/source mode	TAG Metropolitan diversion factors	Normalised weighted averages from CCA RUIS	TAG Metropolitan re-normalised to match CCA estimates
Car	11%	24%	24%
Taxi	8%		6%
Bus	19%		14%
Rail	14%		10%
Light Rail	12%		9%
Walk	19%		14%
Subtotal non-car modes	**72%**	**53%**	**53%**
No Travel	17%	23%	23%

For non-infrastructure interventions, the individual diversion factors from car from Woodcock et al. (2014), Murphy and Usher (2015), and Cycling UK (2021) may be offered to analysts for consideration as an indicative sense check on bespoke figures derived by analysts. These car to cycle diversion factors are respectively 2% (for the London cycle hire scheme), 20% (for the Dublin cycle hire scheme) and 38% (for cycle maintenance provision, which took place during the Covid-19 lockdown periods).

Limitations and future requirements

The published evidence base on the specific issue of estimating marginal cycling diversion factors in UK contexts appears very limited. There remains a need to develop published UK evidence on the following:

1. cycling diversion factors outside cities;
2. how cycling diversion factors vary by baseline mode share and journey purpose;
3. how cycling diversion factors vary by trip length;
4. how cycling diversion factors disaggregate by ‘transfer from’ modes;
5. how cycling diversion factors vary by intervention type; and
6. how cycling diversion factors vary over the short and long run.

Observational surveys (such as RUIS) of behaviour of the same individuals before (retrospectively) and after scheme implementation are recommended as the most appropriate mechanism to measure marginal cycling diversion factors. Such surveys should be included in monitoring and evaluation plans. There are issues with such RUIS that can be mitigated through survey design as considered below:

1. Sample sizes need to be large such that a sufficiently large number of *new* (as opposed to re-routed) cycle trips are captured.
2. Knowledge of the characteristics of the population of cyclists in a local area is required to evaluate the extent to which RUIS samples are representative of this population.
3. Results from self-reported surveys ought to be verified against objective indicators of changes in the volume of cycle traffic and general traffic.
4. It would be best practice to undertake RUIS at several time points following interventions to understand whether transfer to cycling has been maintained, increased or reduced over the longer term.

Considerations for e-cycles

E-cycles need to be treated separately in analyses of benefits associated with cycling interventions since the user and usage profiles of e-cycles are different to the user and usage profiles of conventional cycles. This is because e-cycles have longer ranges, require lower levels of physical exertion and are a new technology.

It is not currently possible to provide clear evidence based recommendations on e-cycle diversion factors since the adoption of e-cycles remains at an early stage and evidence on mode shift to e-cycles will change over time as e-cycle ownership and use increases.

International evidence uncovered through the review suggests that car to e-cycle diversion factors can be expected to be higher than car to conventional cycle diversion factors – examples of car to e-cycle diversion factors were found to range between 25% to 46%, with an indicative mean value of 40%.

An important distinction to make however, is that these e-cycle diversion factors are in response to the acquisition of an e-cycle rather than a cycling intervention and in this sense they should be treated as average rather than marginal diversion factors.

Overall, there is a need for further research to inform how the uptake of e-cycles should be considered in scheme appraisal. Specifically there is a need for evidence on:

1. How e-cycle ownership is changing over time and how this is distributed across population groups;
2. How e-cycle use is changing over time, how e-cycles substitute for other modes, and how e-cycle mode share varies by trip distance; and
3. How e-cycle owners respond to interventions designed to increase cycling, such that marginal e-cycle diversion factors may be estimated.

It is recommended that all road user intercept surveys should include measures of cycle type to enable disaggregation of diversion factors by conventional cycle / e-cycle. An issue at the current time, however, is that the numbers of e-cycle users using new infrastructure may still be small, making it difficult to generate sufficient sample sizes to enable the estimation of marginal e-cycle diversion factors.

1 Introduction

This report summarises findings from a rapid evidence assessment which set out to address the following objectives:

1. To identify and evaluate evidence on cycling diversion factors of relevance to the UK context; and
2. To recommend a revised set of cycling diversion factors for inclusion in Transport Appraisal Guidance (TAG).

The review was commissioned in February 2022 through the Local & Regional Transport Analysis Evaluation Research Support Contract (ERSC) for the Department for Transport (DfT), held by the University of the West of England with Sustrans, Transport for Quality of Life and the University of Westminster (the 'ERSC consortium').

2 Cycling diversion factors and scheme appraisal

Cycling diversion factors represent estimates of the percentage of any *additional* cycling trips which have shifted from other modes, or are trips that were not otherwise made, and which may be associated with investment in cycling (for example, new or enhanced infrastructure or behaviour change measures). These are termed **marginal diversion factors**.

Marginal cycling diversion factors are used in transport appraisal in England (as described in Transport Appraisal Guidance (TAG) unit A.5.1 (DfT, 2020)) as a means of estimating decongestion and other environmental benefits arising from active travel interventions expected to prompt modal shift towards cycling. Emphasis is placed on estimating as accurately as possible the shift from car travel, because in appraisal, the largest proportion of benefits result from a shift from this mode.

Marginal diversion factors are not the same as average diversion factors, which are the percentage of existing cyclists' who would, if cycling were not available, otherwise travel by other modes.

Cycling diversion factors in TAG

The current cycling diversion factors presented in the TAG databook (table A5.4.7, (DfT, 2022)) are shown in Table 4. The cycling diversion factor of 0.11 for car to cycle (for metropolitan areas with a multi-modal choice set) indicates that for every 100 additional cycle trips generated as result of an intervention, 11 are estimated to have transferred from car. This is an average value and is an estimate subject to uncertainty.

The diversion factors currently presented in TAG were drawn from an earlier evidence assessment reported in Dunkerley et al. (2018) and there are some known limitations of the underpinning evidence base and applicability of the diversion factors, as noted in TAG unit A.5.1 (DfT, 2020, paragraph 3.7.11):

“The literature review only found sufficient evidence to estimate values for metropolitan areas and we would expect diversion factor to differ based on the length and purpose of the trip.”

Table 4: Current TAG cycling diversion factors

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 (number of studies)	**33**	
Source: DfT (2022), table A5.4.7		

Dunkerley et al. (2018) identify two further limitations: (i) the cycling diversion factors were drawn from 33 studies, and a quarter of these studies were located outside of the UK (the geographic scope was limited to Europe, USA, Canada, Australia and New Zealand); and (ii) the diversion factors for taxi and no travel are based on only one data point. These deficiencies in the underpinning evidence base provided the impetus for the updated evidence assessment reported here.

Note that the 33 studies underpinning the cycling diversion factors currently on TAG are not listed in Dunkerley et al. (2018) and, at the time of writing, it has not been possible to a identify bibliographies for them. Hence it has not been possible to compare the evidence generated by this updated evidence review with the evidence underpinning the current TAG cycling diversion factors. The types of investment in cycling which were the subject of these studies is also not detailed in the report.

3 Evidence on conventional cycle diversion factors

The review focussed on identifying evidence on diversion factors for conventional cycles and this is considered in this section. Emerging evidence on the adoption and modal shift effects of e-cycles is dealt with through a separate search and evaluation strategy and this is reported in section 4.

3.1 Evidence search strategy

The search for evidence on conventional cycles combined direct requests for relevant literature, made by the Department for Transport (DfT) and UWE teams, with an online search. The direct requests sought to identify sources such as scheme evaluations that may not be published in on-line reports and are a means of drawing on the knowledge of practitioner and academic experts in the field. DfT contacted transport authorities and other organisations involved in the promotion of cycling interventions. UWE made requests for literature on the Universities' Transport Study Group (UTSG) and Cycling and Society Research Group (CSRG) academic email lists and made direct approaches to academics specialising in cycling research. These direct requests for evidence generated 45 sources for screening and shortlisting (Table 5).

The on-line search started with a targeted search for relevant papers arising from cycling research known to the project team. These included studies linked to the Sustrans Connect2 infrastructure projects (MRC 2022), the Cambridgeshire Guided Busway (e.g. Heinen et al. 2015) and studies of cycling interventions in London (e.g. Aldred and Croft 2019).

A keyword on-line search for UK and international evidence was then performed within the main database sources for transport research and which are included in the search engine of the University of the West of England, Bristol (UWE) library catalogue: Science Direct, Scopus, Taylor and Francis and Emerald Publishing. Potentially relevant literature published in 2000 and after was identified from paper titles and abstracts and logged. The online search returned 42 sources for screening and shortlisting (Table 5).

Table 5: Outcomes of the evidence search and screening process

Search component	Sources returned for screening	Sources selected for review	UK / International
Direct requests by DfT and UWE	45	12	10 / 2
Online search	42	8	5 / 3
Subtotal	87	20	15 / 5
Literature reviews	6	6	1 / 5
Total	**93**	**26**	**16 / 10**

Shortlisting

The 87 sources were then screened and shortlisted for inclusion according to the following criteria:

1. The study was based in the UK;
2. The study presented direct evidence of cycling diversion factors; or
3. The study presented evidence of modal shift to cycling from which there may be potential to estimate cycling diversion factors.

UK studies were prioritised because this is of most relevance as a basis for estimating an updated set of cycling diversion factors for settlements in England (the geographic jurisdiction to which TAG applies).

The screening process returned 15 UK sources for inclusion in the review. This limited number arose because, although there is a wide body of research on factors associated with cycling behaviour, there are few studies that provide useable evidence specifically on cycling diversion factors. As this was limited in number and scope, five of the most salient international studies were added to the shortlisted article list as a means of benchmarking evidence on UK cycling diversion factors against evidence from Denmark, Norway, USA and Ireland.

Finally, six international review papers were also evaluated and summarised to check and confirm the finding that there are few published studies reporting direct evidence of marginal cycling diversion factors.

3.2 Evidence review

This section summarises the 20 studies selected for review (i.e. excluding the review papers). The 15 UK sources of evidence are dealt with in three sections relating to the types of methods that have been used to estimate cycling diversion factors, namely:

1. Direct observations of cycling diversion factors (6 sources – evidence summary tables provided as appendix A);
2. Modelling using National Travel Survey data (4 sources – evidence summary tables provided as appendix B); and
3. Modelling using data on relative change in mode share (5 sources – evidence summary tables provided as appendix C).

This is followed by a section summarising the five international studies (evidence summary tables provided as appendix D).

The studies are summarised in each section in alphabetical order by first author surname. The summaries include a qualitatively justified decision ('included in the sift' - yes / no) on whether the evidence has been taken forward to the evaluation of recommended diversion factors for use in TAG, which is explained in section 3.3. Note that not all of the sources that are taken forward are used in the calculations of revised diversion factors. There are a small number of studies that have been retained as providing evidence 'for consideration' as they provide illustrative examples of transfer to cycling in response to non-infrastructure intervention. Further details on how the studies 'included in the sift' have been dealt with are provided in section 3.3.

Direct observation of cycling diversion factors (6 sources)

The six studies in the category of direct observation of cycling diversion factors have employed research instruments designed to generate primary data on the proportion of cycle trips that would otherwise have been undertaken by another mode of transport. Some of, but not all of, these studies are linked to a cycling intervention of some form.

- **Aldred and Croft (2019)** undertook an exploratory small-scale road user intercept survey after a modal filter had been installed on a single residential street in London. The survey revealed an additional 27 cyclists on the street, 6 of whom suggested they would have used another mode of transport had the modal filter been removed.

  Included in sift for diversion factor recommendations: No. This article did not report the mode of transport that the cyclists had transferred from and the sample is in any case too small to derive a meaningful estimation of a percentage diversion factor from other modes to cycling.

- **Cycling UK (2021)** report on a before and after survey of individuals that had accessed Dr Bike maintenance support during the Covid-19 pandemic. The survey revealed that 38% of new cycle trips had diverted from car (Cycling UK, 2021). Car to cycle diversion factors are also shown to vary by journey purpose (Table 6) and range from a lower limit of 27% for work journeys to 48% for visiting friends and family.

Table 6: Marginal diversion factors in response to Dr Bike maintenance, by journey purpose

Journey purpose	New trips now regularly made by bike	%age previously made by car	Number previously made by car
Work	930	27%	251
Education	684	42%	287
Shopping	2,777	36%	1,000
Other trips	4,976	34%	1,692
Visit friends and family	3,778	48%	1,813
Other leisure activities	7,482	36%	2,694
Total	**20,627**	**38%**	**7,737**

Source: Cycling UK (2021)

Included in sift for diversion factor recommendations: Yes. The study is one of only three sources that provides an indication of diversion factors for non-infrastructure interventions. However, the evidence needs to be carefully interpreted since the intervention took place during the Covid-19 pandemic lockdown periods when propensity to use public transport significantly reduced, as did general traffic levels. The 38% diversion factor in response to Dr Bike maintenance interventions is therefore likely to be higher than under normal circumstances. The evidence nevertheless provide an indication of the upper limit on cycling diversion factors in response to Dr Bike maintenance interventions and provides confirmation that diversion factors are likely to vary by journey purpose.

- **Nankivell (2021) and Panagiotis (2019)** report on an on-line survey of a purposive sample of people living in Greater Manchester. Respondents were asked to report how they undertook existing cycling trips before they started cycling. This revealed an **average** (not marginal) car to cycle diversion factor of 44% as this survey was not linked to an intervention. Diversion factors are disaggregated by journey purpose (see Table 7). This shows that car to cycle average diversion factors range from 25% for education up to 55% for shopping. The variation in diversion factors by journey purpose may be influenced by the baseline car mode share for that trip purpose. For example, if the baseline car modal share is low for education trips, then there is low potential for transfer from car to cycling.

Table 7: Average diversion factors in Greater Manchester, by journey purpose

	Percentage transfer from source modes to cycling						
Trip purposes	**Car**	**Taxi**	**Bus**	**Train**	**Tram**	**Walking**	**Not going out**
Business	51%	0%	17%	9%	6%	7%	10%
Shopping	55%	0%	13%	3%	3%	24%	3%
Visiting friends	49%	1%	16%	4%	13%	16%	2%
Holidays and leisure trips	54%	1%	2%	17%	2%	7%	17%
Commuting	38%	0%	23%	13%	14%	7%	4%
Personal business	36%	0%	16%	4%	7%	35%	3%
Escort others to school/education	35%	0%	3%	0%	0%	45%	17%
Sport and events	35%	7%	23%	10%	15%	8%	2%
Education	25%	0%	41%	2%	11%	14%	7%
Average (of survey population)	**44%**	**1%**	**16%**	**8%**	**9%**	**16%**	**7%**
Source: Nankivell (2021)							

Included in sift for diversion factor recommendations: No. This study reports average rather than marginal diversion factors, and this is because they relate to substitute modes for existing cycling trips, rather than new cycling trips linked to interventions. This means they are not valid in the context of estimating changes in externalities resulting from cycling interventions. These average diversion factors are significantly higher than the observed marginal diversion factors linked to cycling infrastructure interventions reported in Sloman et al. (2021) and described in the next paragraph. To be specific, the 44% overall average car to cycle diversion factor reported by Nankivell (2021) compares with a 26% marginal car to cycle diversion factor linked to infrastructure interventions reported by Sloman et al. (2021). Nevertheless, the study provides insight into the extent to which diversion factors vary by journey purpose.

- **Sloman et al. (2021)** report on road user intercept surveys (RUIS) employed in seven cities in England where infrastructure improvements (cycle lanes and junction treatments) had been delivered through the Cycle City Ambition (CCA) fund programme. Cyclists using new or improved infrastructure were asked to report how they would travel if the scheme were not available.
    - The RUIS revealed a car to cycle diversion factor of 26% when the RUIS data is pooled across all seven programme areas.
    - Car to cycle diversion factors vary between cities and ranged between 12% and 40% (excluding Oxford due to the sample size of 4 – see Table 8).

Table 8: Cycle city ambition fund cycling diversion factors from RUIS

City	Year of survey	No. of new cycle trips recorded (n)	Percentage transfer from car	Percentage transfer from other modes	Percentage new trips
Birmingham	2017	184	19%	37%	45%
Greater Manchester	2019	19	37%	32%	31%
Newcastle	2017	60	12%	55%	33%
Norwich	2017	131	32%	65%	2%
Norwich	2018-19	208	40%	55%	5%
Oxford	2016	4	0%	74%	26%
West of England	2016	30	37%	50%	13%
West of England	2017	18	33%	67%	0%
West Yorkshire	2017-18	100	18%	72%	10%
Programme		**593**	**26%**	**52%**	**22%**
Source: Sloman et al (2021)					

Included in sift for diversion factor recommendations: Yes. This evidence is directly applicable to TAG as it provides observed marginal diversion factors from across England, connected with cities of different size and type, and linked with a range of types of route and junction intervention. Hence, by its nature, it is not location or intervention specific. It therefore offers the prospect of providing a good basis for the estimation of typical marginal diversion factors.

- **Woodcock et al. (2014)** report on a survey of users of the London Cycle Hire system. This revealed that about 2% of new cycle trips had diverted from car (Table 9). This low level of modal transfer from car is indicative of the low baseline rates of car use observed in inner London, and which is a unique urban environment in England terms of density of development, constraints on road space and high levels of public transport supply.

  Included in sift for diversion factor recommendations: Yes. The study is one of only three sources that provides observed, marginal diversion factors for a non-infrastructure intervention – cycle hire systems. However, the inner city London context is unique and the diversion factors revealed can only be applied to this London context.

Table 9: Cycling diversion factors estimated for London cycle hire scheme

Alternative main mode	Percentage modal transfer excluding own bike
No travel	9.7%
Own bike	-
Walking	32.8%
Bus	19.4%
Underground	29.3%
Train or light rail	2.3%
Taxi or mini cab	3.3%
Car or van	1.9%
Motorcycle / moped / scooter	0.6%
Other	0.6%
Total	100.0%
Source: Woodcock et al. (2014)	

Modelling using National Travel Survey data (4 sources)

Four sources (Bearman and Singleton 2014, Lovelace et al. 2011, Sloman et al. 2020, Steer Davies Gleave 2015) report on modelling approaches using National Travel Survey (NTS) data to infer cycling diversion factors.

- **Lovelace et al. (2011)** consider assumptions that (i) new cycling trips will reflect the same journey purpose distribution as existing trips and (ii) that new cycling trips will divert from other modes in the same proportions as the modal share for existing trips. An analysis of 2008 NTS data undertaken on this basis suggests a car driver to cycle diversion factor of 45%; and a car passenger to cycle diversion factor of 22%. Bearman and Singleton (2014) draw on the diversion factor given by Lovelace et al. (2011) in order to estimate carbon savings for modal transfer from car to cycle for travel to school. No additional theoretical or empirical insights into cycling diversion factors are provided by Bearman and Singleton (2014).

  Included in sift for diversion factor recommendations: No. The modelling method is well considered, and based on good quality data, but there is no empirical basis for the assumption that new cycling trips will divert from other modes in the same proportions as the modal share for existing trips. The estimates are not validated against observations and are therefore of less value than the direct observations evaluated in the previous section. Indeed, the car to cycle diversion factors estimated through this modelling approach are significantly higher than the observed marginal diversion factors reported in Sloman et al. (2021).

- **Sloman et al. (2020)** employ a similar set of assumptions and method to Lovelace et al. (2011) using 2019 NTS data, but make an adjustment to account for an assumed 4% of new cycle trips diverting from ‘no travel’. This analysis suggests a car driver to cycle diversion factor of 40% and a car passenger to cycle diversion factor of 22%, and are hence similar to the estimates derived by Lovelace et al. (2011).

Included in sift for diversion factor recommendations: No. The modelling method is well considered, and based on good quality data, but there is no empirical evidence for the assumption that new cycling trips will divert from other modes in the same proportions as the modal share for existing trips. The predictions are not validated against observation and are therefore of less value than the direct observations evaluated in the previous section. The car to cycle diversion factors estimated through this approach are significantly higher than the observed marginal diversion factors reported in Sloman et al. (2021). This may be because the diversion factors are estimated from the mode share distribution for all journey lengths. Car mode shares are lower for the shorter journeys, and it is shorter journeys that are suited to cycling. Car mode shares do, however, increase steeply as distance increases. For example, the NTS 2019 data indicates an 18% car mode share for journeys under 1 mile, rising to 29% car mode share for journeys between 1 and 2 miles.

- **Steer Davies Gleave (2015)** estimated a car to cycle diversion factor of 12% for travel to secondary schools in Hertfordshire following the implementation of Bikeability training. This estimate is based on an assumption that half of the 23.5% of trips to school by car (revealed by the NTS travel to school mode share averaged over 2008 to 2013) would transfer to cycling. However, there is no empirical evidence to support this assumption.

  Included in sift for diversion factor recommendations: No. The 12% estimate is based on a 'what-if' scenario which was reasonable for the application to which is was put by Steer Davies Gleave (2015) (an estimate of wider economic benefits), but the assumed diversion factor has no empirical basis.

Modelling using data on relative change in mode share (5 sources)

There is a body of literature on modal transfer to cycling which considers indicators such as change in mode share, but for which diversion factors have not been estimated or included in the published article. Five sources of this type were included in the review to investigate whether it would be possible to infer diversion factors from published evidence of change in modal share (Bartle and Chatterjee 2017, Heinen et al. 2015, Sloman et al. 2018, Sloman et al 2009, and Song et al. 2017). However, this was not found to be possible as is now explained.

Lovelace et al. (2011) evaluate an indicator termed the replacement ratio (RR) which is defined as:

$$RR = \text{change in bicycle trips} / \text{change in car trips}$$

It is noted that "the replacement ratio can be interpreted as the number of additional bicycle trips required to replace or prevent a single car trip".

The reciprocal of the replacement ratio could theoretically be interpreted as the number of car trips avoided for every additional cycle trip. This provides a potential means of estimating diversion factors where data on a change in modal share is available. However, there are issues with this approach.

To take an illustrative example to explain the method used, Sloman et al. (2009) report change in modal share from a before and after (hands-up) survey of schools in which 'Bike It' training for children had been provided. This is a repeated cross-sectional survey approach, which does not provide information on how the same individuals have changed behaviour between two points in time. The replacement ratio approach could be used to estimate a theoretical diversion factor, applying the following logic:

- The surveys revealed that the number of car trips to school had reduced by 1.4 percentage points while at the same time cycling trips to school had increased by 7.3 percentage points.
- In other words, to achieve a 7.3 percentage point increase in cycle trips in this instance, there needed to be a concurrent reduction in car trips of 1.4 percentage points
- It follows that a 1 percentage point increase in cycle trips would be associated with 1.4 / 7.3 = 0.19 fewer car trips
- Hence it can be inferred that 100 additional cycle trips would be associated with 1.4 / 7.3 x 100 fewer car trips - a diversion factor of 19%.

Four other sources which evaluated changes in modal share for cycling following interventions were examined:

- Bartle and Chatterjee (2017) and Sloman et al. (2018) which involved evaluations of different aspects of the Local Sustainable Transport Fund initiatives aimed at boosting cycling rates.
- Song et al's (2017) evaluation of mode shift following implementation of cycling infrastructure in Cardiff, Southampton and Kenilworth (part of the Connect 2 programme).
- Heinen et al's (2015) study on change in mode of travel to work for residents living close to the Cambridgeshire busway which included new walking and cycling routes.

While different forms of change in mode share evidence are reported in these articles (as is common in the wider body of research on cycling behaviour) none of the studies directly analysed or reported diversion factors.

Included in sift for diversion factor recommendations: No. Use of the replacement ratio method cannot be used to derive diversion factors from change in mode share indicators because these only consider the gross change in the mode share. One issue is that the use of percentage point changes in the replacement ratio does not take into account the baseline mode share (which is likely to differ between modes), and this calls into question the validity of the measure. Taking the example replacement ratio described above, if car trips are 10,000 in the base and cycle trips are 100, a 1.4% reduction in car trips is 140 trips and a 7.3% increase in cycle trips is 7.3 trips. Combining those gives a diversion factor estimate of 7.3/140 which is about 5% - a lot lower than the estimate based on percentage point changes.

A second issue is that other modes exist, and the change at the gross level for, for example driving, results from switches away from driving to cycle and other modes and switches to driving from other modes. There is no information at the individual level on where the person driving is switching to.

To illustrate the problem, Table 10 indicates two change scenarios, A and B. In Change A and B the gross before and after percentages of trips for three modes are the same. For example, the car mode share changes from 45% to 40% (see total before and total after in Table 10). However, for Change A the diversion factor from Car to Cycle is 1 out of 3 new cycling trips, or 33%, and in Change B it is 2 out of 3 new trips or 67%. The gross mode share approach would give the same diversion factor however. For this reason, wider research that reports changes in mode share resulting from cycling interventions has been screened out of this present review.

Table 10: Illustrative comparison of gross and net change in mode share

To:	Car	Walk	Cycle	Total Before
Change A, from:				
Car	40	4	1	**45**
Walk	0	33	2	**35**
Cycle	0	1	19	**20**
Total After	**40**	**38**	**22**	**100**
Change B, from				
Car	38	5	2	**45**
Walk	1	33	1	**35**
Cycle	1	0	19	**20**
Total After	**40**	**38**	**22**	**100**

International evidence on conventional cycle diversion factors (5 sources)

The following five international sources were examined as they were identified as providing informative direct evidence of marginal cycling diversion factors, for the purposes of benchmarking in four cases (Cycle Superhighway (2019), Matute et al. (2016), Monsere et al. (2014), Murphy and Usher (2015)). Flugel et al. (2018) provided an informative review of diversion factor estimation methods, and included a literature review examining the quality and extent of diversion factor evidence.

- **Cycle Superhighway (2019)** report car to cyclist diversion factors for 8 cycle superhighways in Denmark. The cycle superhighways have been designed to enable cycling across municipal borders. The percentage of cyclists on the superhighways observed to be transferring from car ranged from 9% to 26% (Table 11).

Table 11: Change in cycling and mode transfer from car for Danish cycle superhighways

Route	Percentage change in number of cyclists	Percentage of new cyclists transferring from car
Albertslund Route C99 (18km)	14% from 2010 to 2018	10%
Allerod Route C93 (30 km)	14% from 2010 to 2018	14%
The Farum Route C95 (21 km)	68% from 2010 to 2018	26%
The Frederikssund Route C97 (43 km)	15% from 2010 to 2018	12%
Inner Ring Route C94 (14 km)	21% from 2010 to 2018	21%
The Ishoj Route C77 (14 km)	2% from 2010 to 2018	25%
Ring 4 Route C84 (20km)	12% from 2010 to 2018	12%
The Vaerlose Route C83 (8km)	20% from 2010 to 2018	9%
Source: Cycle Superhighway (2019)		

Included in sift for diversion factor recommendations: No. This is a summary report and the detailed scheme evaluation and data collection methodologies are not described. The Danish cycling context is also different to the UK. The diversion factors nevertheless provide a means of benchmarking the recommendations described in section 3.3.

- **Flugel et al. (2018)** report on a modelling exercise designed to understand factors associated with cross-modal substitution. Over 10,000 diversion factors are simulated, using a mode choice model. Scenarios are developed to simulate change in mode share if the generalised cost of travel by car, train, bus or metro is altered. The change in mode share is used to estimate diversion factors. This analysis indicated, for example, that for journeys under 5km, 15.5% of trips switching away from car would be expected to divert to cycling. Note that this is not a cycling diversion factor as the figure does not represent the proportion of new cycling trips that have transferred another mode. A regression analysis is used to identify factors associated with variation in diversion factors. It is noted that "diversion factors to cycling tend to be higher for work-related trips"

  Included in sift for diversion factor recommendations: No. The study does not report marginal cycling diversion factors, and is based on a simulation method rather than on observation.

- **Matute et al. (2016)** report on road user intercept surveys (dismount surveys and online surveys advertised by poster) performed at 20 locations in Los Angeles, where upgraded cycling infrastructure had been implemented in the previous two year period and were at least 1.2km long. Cyclists were asked to report how they would travel if the bike lane did not exist. Car to cycle diversion factors were found to range between 13% and 33% (Table 12)

Table 12: Cycling diversion factors linked to infrastructure improvements in Los Angeles, USA

Transfer from mode	Non-dismount Poster Survey	Dismount survey (all)	Dismount survey (class 2)	Dismount survey (class 4)
Take bus	24.3%	19.4%	44.0%	8.3%
Use car	13.2%	33.3%	28.0%	35.4%
Not take this trip	50.7%	34.7%	24.0%	39.6%
Other	11.8%	12.5%	4.0%	16.7%
n	67	51	22	27

Notes: Class refers to cycle lane grade. Higher numbers reflect greater level of service
Source: Matute et al. (2016)

Included in sift for diversion factor recommendations: No. International evidence cannot be assumed to be transferable to the UK context. In this case, for instance, an atypically high proportion - 63% of cyclists - reported using the infrastructure for recreational purposes. The diversion factors nevertheless provide a means of benchmarking the recommendations described in section 3.3.

- **Monsere et al. (2014)** report on road user intercept surveys conducted along eight new protected bike lanes implemented across five US cities. The marginal diversion factors are reported in Table 13, but there are significant limitations. The number of new cyclists transferring from other modes was small (141 out of 1316 cyclists intercepted) and hence the sample sizes for individual locations are also very small. The 'transfer from' modes are also not reported and hence it is not possible to derive meaningful diversion factors from this data set (Table 13).

Included in sift for diversion factor recommendations: No. International evidence cannot be assumed to be transferable to the UK context. In this case, it is also not possible to derive meaningful car to cycle diversion factors.

Table 13: Cycling diversion factors linked to infrastructure improvements across 5 US cities

Consider the trip you were making when you were handed the postcard. Before the facility was built, how would you have made this trip?				
	Route	By other mode	Would not have taken trip	New cycling trips
Austin	Barton Springs	100%	0%	1
	Rio Grande	100%	0%	3
Chicago	Dearborn	91%	9%	28
	Milwaukee	91%	9%	25
Portland	NE Multnomah	100%	0%	11
San Francisco	Oak Street	86%	14%	17
	Fell Street	88%	13%	20
Washington DC	L Street	83%	17%	36
	Total	89%	11%	141

Source: Monsere et al. (2014)

- **Murphy and Usher (2015)** report on a survey of users of the Dublin city centre bicycle sharing system (Dublinbike). Respondents were asked to report the mode of transport that the Dublin bike was substituting for. The survey indicates a car to bike share diversion factor of circa 20% (Table 14).

Table 14: Mode of transport used prior to using the Dublinbike scheme

Alternate mode	Percentage
Car	20%
Bus	26%
Rail	9%
Walking	46%
Total	100%

Source: Murphy and Usher (2016)

Included in sift for diversion factor recommendations: Yes. The UK evidence review provided very limited evidence of diversion factors for non-infrastructure schemes and this study provides an additional indication of diversion factors for bicycle sharing systems outside of London. The Dublin context is similar to UK cities.

Summary of the extent of evidence

The evidence assessment suggests that the number of UK based published studies available from which to estimate conventional cycle marginal diversion factors is small. This outcome was checked and confirmed through a further evaluation of six international review papers (Panter et al., 2019, Pucher et al., 2010, Scheepers et al. 2014, Wardman et al. 2018, Handy et al. 2014 and Iyer et al. 2019), and which are summarised in Appendix E. These six literature reviews returned only one additional, but superseded source of evidence on UK cycling diversion factors. (Noland and Ishaque (2006) – which reports on a short term cycle hire scheme in London, and which has been superseded by the current system evaluated by Woodcock et al. (2014)). Indeed Flugel et al. (2018) also identified that “the literature on diversion factors is limited”.

Table 15 provides an overview of car to cycle diversion factors extracted from the 20 reviewed sources (excluding the literature reviews) and indicates which studies have been taken forward to the evaluation of recommended diversion factors for inclusion in TAG, explained in section 3.3.

Table 15: Summary of car to cycle diversion factors extracted from reviewed sources

Source	Location	Intervention type	Survey Data Year	Survey / analysis type	Reported car to cycle diversion factor	Sample size	Included in diversion factor recommendations
UK - Direct observation of cycling diversion factors							
Aldred and Croft (2019)	London	Modal filter	2017	Road user intercept survey	None	27	No
Cycling UK (2021)	England (national)	Dr Bike maintenance sessions	2020 to 2021	Observed from online survey of Dr Bike users. Respondents asked “How do you normally travel for the following journey purposes” before and after Dr Bike engagement	38%	20,627 trips	Yes
Nankivell (2021) and Panagiotis (2019)	Greater Manchester	None	2021	Observed from online survey of local residents “What trips do you regularly make by bike?” “How did you make that trip before starting cycling?”	44%	603 people 1839 trips	No
Sloman et al. (2021)	Birmingham	Cycle lanes and junction treatments (cycle city ambition funded)	2017	Observed from RUIS “How would you travel if this scheme was not available?”	19%	184 people	Yes
Sloman et al. (2021)	Greater Manchester	Cycle lanes and junction treatments (cycle city ambition funded)	2019	Observed from RUIS “How would you travel if this scheme was not available?”	37%	19 people	Yes
Sloman et al. (2021)	Newcastle	Cycle lanes and junction treatments (cycle city ambition funded)	2017	Observed from RUIS “How would you travel if this scheme was not available?”	12%	60 people	Yes
Sloman et al. (2021)	Norwich	Cycle lanes and junction treatments	2017	Observed from RUIS “How would you travel if this scheme was not available?”	32%	131 people	Yes

Source	Location	Intervention type	Survey Data Year	Survey / analysis type	Reported car to cycle diversion factor	Sample size	Included in diversion factor recommendations
		(cycle city ambition funded)					
Sloman et al. (2021)	Norwich	Cycle lanes and junction treatments (cycle city ambition funded)	2018-19	Observed from RUIS "How would you travel if this scheme was not available?"	40%	208 people	Yes
Sloman et al. (2021)	Oxford	Cycle lanes and junction treatments (cycle city ambition funded)	2016	Observed from RUIS "How would you travel if this scheme was not available?"	0%	4 people	Yes
Sloman et al. (2021)	West of England	Cycle lanes and junction treatments (cycle city ambition funded)	2016	Observed from RUIS "How would you travel if this scheme was not available?"	37%	30 people	Yes
Sloman et al. (2021)	West of England	Cycle lanes and junction treatments (cycle city ambition funded)	2017-18	Observed from RUIS "How would you travel if this scheme was not available?"	33%	18 people	Yes
Sloman et al. (2021)	West Yorks	Cycle lanes and junction treatments (cycle city ambition funded)	2017-18	Observed from RUIS "How would you travel if this scheme was not available?"	18%	100 people	Yes
Sloman et al. (2021)	Average over all CCA Programme cities	Cycle lanes and junction treatments (cycle city ambition funded)	2016-19	Observed from RUIS "How would you travel if this scheme was not available?"	26%	593 people	Yes
Woodcock et al. (2014)	London	London bicycle hire system	2011	Observed from survey of cycle hire users combined with annual usage data Respondents asked for "the main mode that would typically have used to make their most recent cycle hire trip before the scheme was available"	2%	2652 people	Yes

Source	Location	Intervention type	Survey Data Year	Survey / analysis type	Reported car to cycle diversion factor	Sample size	Included in diversion factor recommendations
UK - Modelling using National Travel Survey Data							
Lovelace et al. (2011)	GB (average)	None	2008	Modelled from National Travel Survey	45%	993 trips	No
Bearman and Singleton (2014)	GB (average)	None	2008	Modelled from National Travel Survey Based on Lovelace et al. (2011)	45%	-	No
Sloman et al. (2019)	GB (average)	None	2019	Modelled from National Travel Survey data	40%	250 trips	No
Steer Davis Gleeve (2015)	Hertfordshire	Bikeability training for schools	2010	Modelled from survey of children combined with NTS 2008-2013 data	12%	-	No
UK - Modelling using data on relative change in mode share							
Bartle and Chatterjee (2017)	Bristol	Workplace travel planning measures	2014 - 2016	Employee travel to work surveys	None	2014 - 9,684 2016 - 5,823	No
Heinen et al. (2015)	Cambridgeshire	Guided busway with walking and cycling path	2009 - 2012	Annual panel survey of local residents including travel diary	None	470	No
Sloman et al. (2018)	England (12 areas)	Multiple LSTF measures to support non-car travel	Various	Various	None	Various	No
Sloman et al. (2009)	Aylesbury, Brighton, Darlington, Derby, Exeter, Lancaster, Morecambe	Cycling demonstration towns interventions including a Bike-it programme of cycling support	2006 - 2008	Hand-up surveys of school children	19% (inferred)	Baseline: 14,896 Follow-up: 13,200	No
Song et al. (2017)	Cardiff, Southampton, Kenilworth	Walking and cycling infrastructure	2010 - 2012	Before and after intervention postal surveys to measure change in travel behaviour	None	3516	No
International studies							
Cycle Superhighway (2019)	Denmark	Cycle lane infrastructure	2010 to 2018	Unknown	9% to 26%	Unknown	No

Source	Location	Intervention type	Survey Data Year	Survey / analysis type	Reported car to cycle diversion factor	Sample size	Included in diversion factor recommendations
Flugel et al. (2018)	Norway	None	-	Mode choice model	None	14,947 trips	No
Matute et al. (2016)	Los Angeles, USA	Improvement to cycle lanes	2016	Observed from RUIS	13% to 33%	618 people	No
Monsere et al. (2014)	5 US cities	Improvements to cycle lanes	2014	Observed from RUIS	None	141	No
Murphy and Usher (2015)	Dublin	Bicycle hire system	Unknown	User survey	20%	360	Yes

3.3 Recommendations on conventional cycle diversion factors

The evidence assessment identified four UK studies that are suitable for providing guidance on typical marginal cycling diversion factors relating to infrastructure and non-infrastructure interventions. These studies are identified in Table 16.

Table 16: Studies selected as a basis for cycling diversion factor recommendations

Study	Intervention type	Evidence suitable for:
Infrastructure interventions		
Sloman et al. (2021)	Cycle lane and junction treatments in 7 cities in England	Deriving recommended values for typical marginal cycling diversion factors related to infrastructure in cities in England
Non-infrastructure interventions		
Cycling UK (2021)	Cycle maintenance provision	Providing an indication of cycling diversion factors for cycle maintenance provision
Murphy and Usher (2015)	Dublin cycle hire scheme	Providing an indication of cycling diversion factors for cycle hire systems in London
Woodcock et al. (2014)	London cycle hire scheme	Providing an indication of cycling diversion factors for cycle hire systems in London

Cycling diversion factors for infrastructure interventions

The CCA fund evidence reported in Sloman et al. (2021) has strengths in revealing observed marginal diversion factors linked to recently implemented cycling infrastructure schemes across 7 cities in England. A secondary analysis has been performed on the CCA data to

1. Construct 95% confidence intervals around the diversion factor estimates for each city and for the programme area as a whole; and
2. Arrive at a best estimate of typical mean marginal cycling diversion factors by calculating a weighted mean across the 7 RUIS surveys (which accounts for sample size and therefore the degree of uncertainty in each data point).

The method used to calculate the weighted mean marginal diversion factors follows the approach described in Wang (2018) – How to conduct a meta-analysis of proportions. This goes as follows:

Cycling diversion factors from a mode (DF) are calculated as:

$$DF = \frac{k}{n}$$

Where n is the total number of new cycle trips and k is the number of trips diverting from the mode in question. The standard error (SE) of a diversion factor (which is a proportion) may be calculated as:

$$SE = \sqrt{\frac{DF(1 - DF)}{n}}$$

Wang (2018) explains that weights for study i - when contributing to a weighted mean proportion taken across multiple studies - may be calculated as the inverse variance weight (w):

$$w_i = \frac{1}{SE^2} = \frac{n}{DF(1 - DF)}$$

The weighted average (DF_{wav}) diversion factor from a given mode, taken across multiple studies, may finally be estimated as:

$$DF_{wav} = \frac{\sum w_i DF_i}{\sum w_i}$$

In the weighted average calculation, higher weights are attached to diversion factors estimates for which there is greater certainty as reflected in smaller standard errors.

This method has been used to derive the weighted mean marginal diversion factors summarised in Table 17. The weighted mean in the first line is estimated using the methods above. The second row shows the means by simply pooling of the data, as estimated by the authors of the CCA report (Sloman et al., 2021).

Note that Oxford has been excluded from the weighted average analysis because the sample size is too small to provide meaningful information on diversion factors (n=4). Both Norwich surveys have also been excluded from the estimated weighted average for induced cycle trips (i.e. trips that did not happen prior to the infrastructure improvement) because Norwich had atypically low proportions of induced trips compared to the other settlements. The West of England 2017 survey is also excluded from the 'induced trips' weighted average because there are no observations of induced trips out of a small sample size of 18. This means the standard error cannot be calculated. This has no effect on the weighted average as the sample size is small.

Figures 1, 2 and 3 show graphs of the individual diversion factors and their confidence intervals, and the weighted mean and its confidence interval, for diversion to cycle from car, non-car modes, and new trips.

Table 17: Cycle city ambition fund diversion factors and weighted means with confidence intervals

			Percentage transferring from car as driver or passenger				Percentage transferring from other modes				Percentage induced trips			
City	Year of survey	New cycle trips (n)	%	CI lower limit	CI Upper limit	SE	%	CI lower limit	CI Upper limit	SE	%	CI lower limit	CI Upper limit	SE
Weighted mean			**25%**	**22%**	**28%**	**2%**	**55%**	**51%**	**58%**	**2%**	**24%**	**20%**	**28%**	**2%**
Simply pooling		**593**	**26%**	**23%**	**30%**	**2%**	**52%**	**48%**	**56%**	**2%**	**22%**	**18%**	**25%**	**2%**
Birmingham	2017	184	19%	13%	24%	3%	37%	30%	44%	4%	45%	37%	52%	4%
Greater Manchester	2019	19	37%	15%	58%	11%	32%	11%	53%	11%	31%	10%	52%	11%
Newcastle	2017	60	12%	4%	20%	4%	55%	43%	68%	6%	33%	21%	45%	6%
Norwich - 2017	2017	131	32%	24%	40%	4%	65%	57%	74%	4%	2%	0%	5%	1%
Norwich - 2018/19	2018-19	208	40%	33%	47%	3%	55%	48%	62%	3%	5%	2%	8%	1%
Oxford	2016	4	0%	0%	0%	0%	74%	31%	116%	22%	26%	-16%	69%	22%
West of England - 2016	2016	30	37%	19%	54%	9%	50%	32%	68%	9%	13%	1%	25%	6%
West of England - 2017	2017	18	33%	11%	55%	11%	67%	45%	89%	11%	0%	0%	0%	0%
West Yorkshire	2017-18	100	18%	11%	26%	4%	72%	63%	81%	4%	10%	4%	16%	3%

Source Sloman et al. (2021)
CI – Confidence Interval
SE – Standard Error

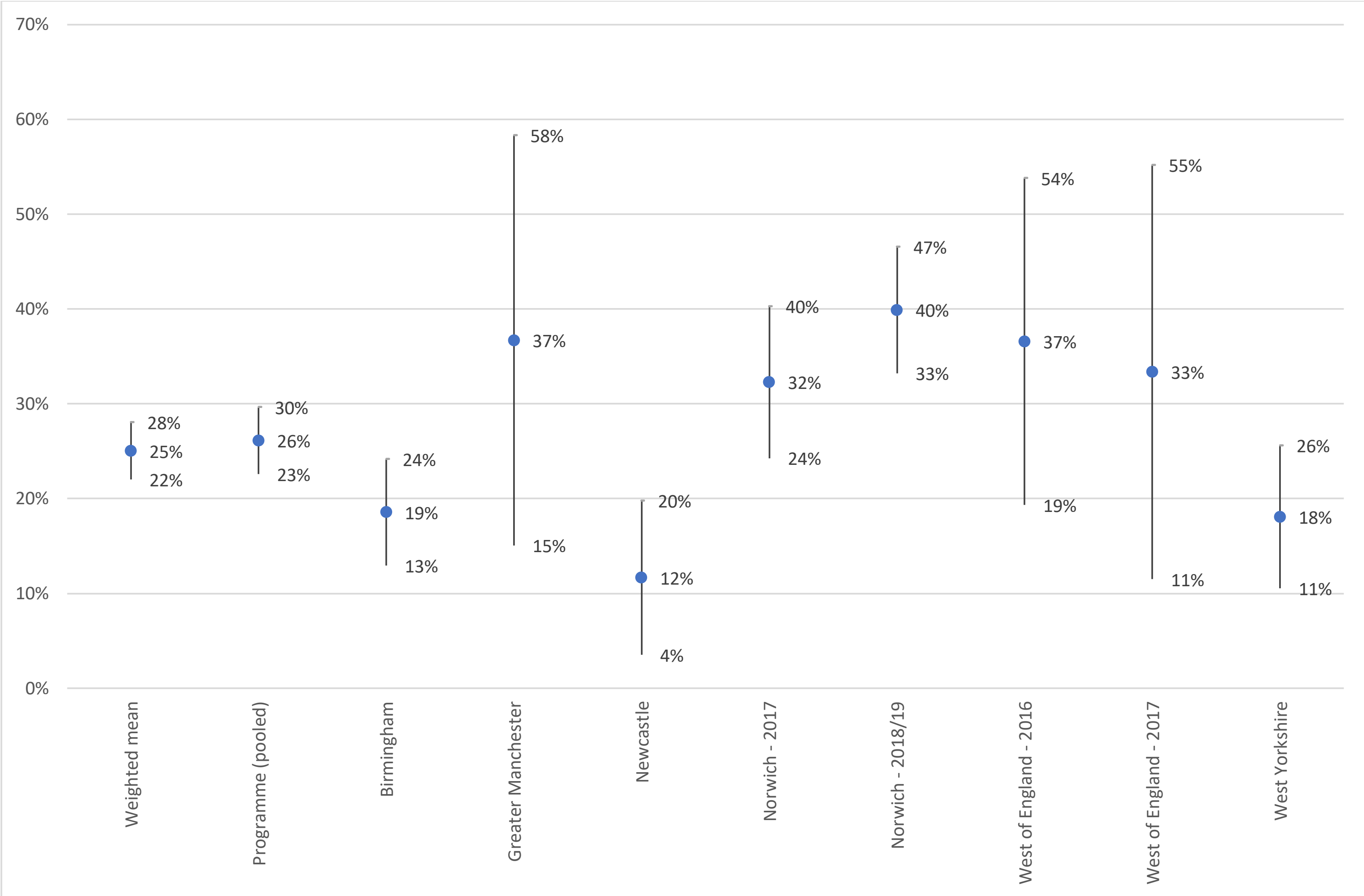

Figure 1: Cycle city ambition fund car to cycle diversion factors with weighted mean and confidence intervals

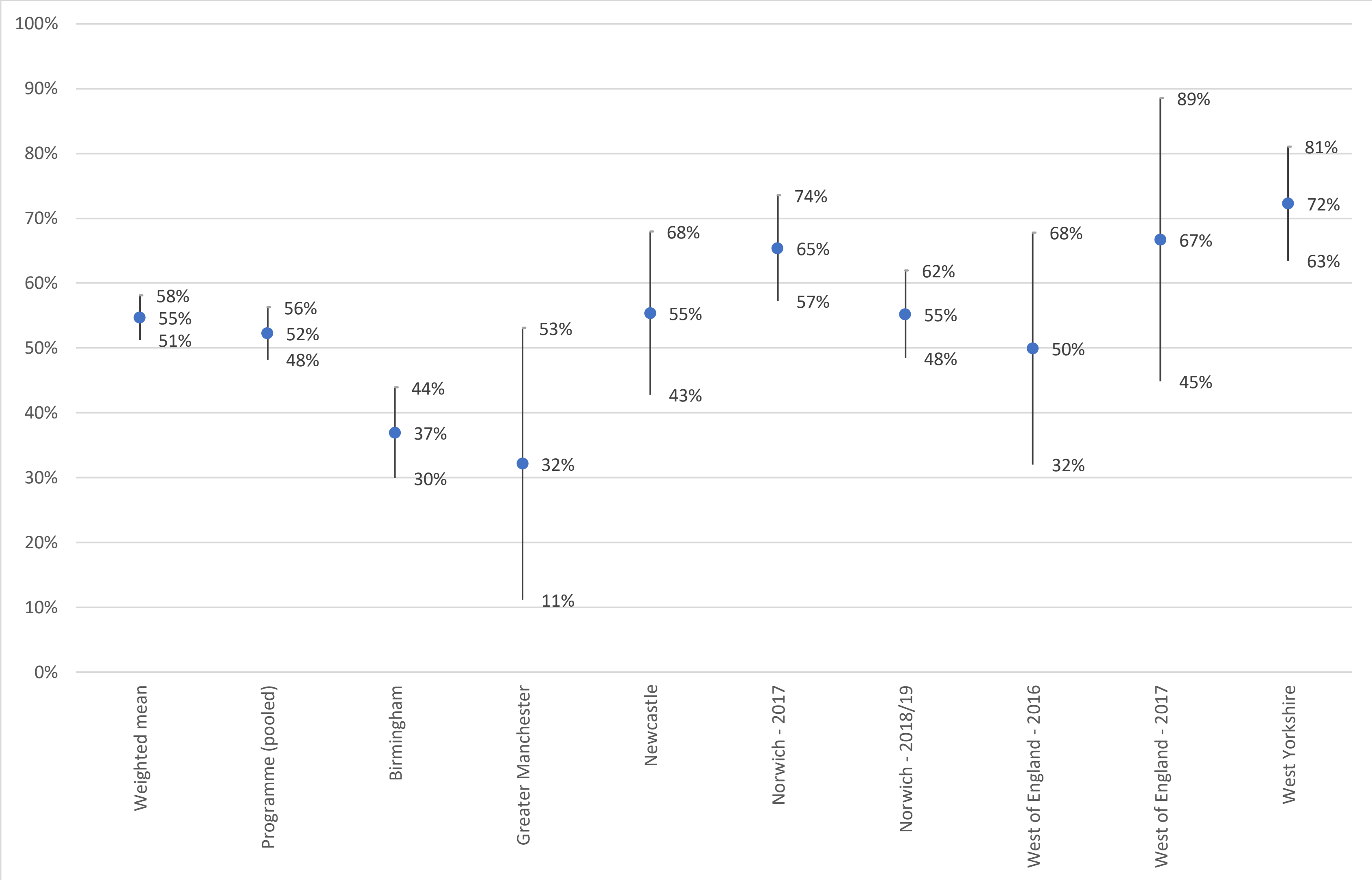

Figure 2: Cycle city ambition fund non-car modes to cycle diversion factors with weighted mean and confidence intervals

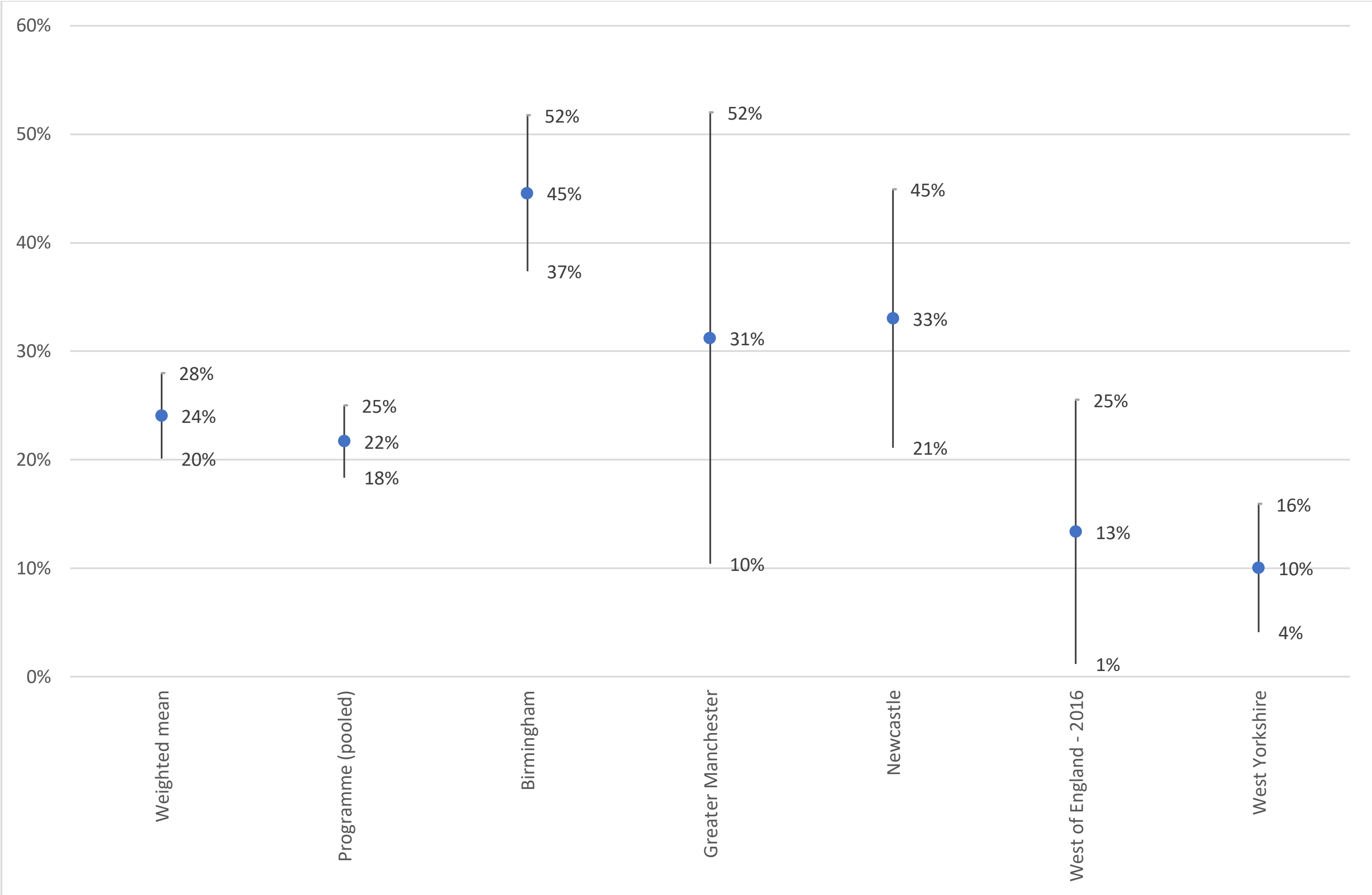

Figure 3: Cycle city ambition fund new trip to cycle diversion factors with weighted mean and confidence intervals

The main observations arising from the method and the results are as follows:

- When pooling the RUIS data across the full CCA programme, the car to cycle diversion factor is estimated to be 26% (CI 23% to 30%).
- The weighted mean car to cycle diversion factor is estimated to be 25% (CI 22% to 28%). The confidence intervals for the programme estimate and weighted mean overlap which confirms a level of consistency between the two results.
- Although there is variation in car to cycle diversion factors between the individual areas (Figure 1), the confidence intervals for the individual cities in most cases overlap with the confidence interval for the weighted mean. This suggests that it is reasonable to interpret the weighted mean (of 25%) as a 'typical' car to cycle diversion factor in response to cycling infrastructure interventions (for example, in the absence of local evidence).

The following observations are made in relation to comparing these latest estimates with previous assessments of cycling diversion factors and international evidence:

- The estimates for car to cycle diversion factors, drawn from the CCA RUIS are higher than (slightly over double) the car to cycle diversion factors currently presented in TAG of 11%. The CCA weighted mean is also higher than the combined TAG diversion factor for car and taxi which is 19%. Note that the CCA surveys did not explicitly ask respondents to specify whether they transferred from taxi and such responses could have been categorised as either 'car as passenger' or 'other'. It is considered more likely that survey respondents would have treated 'taxi' as 'other mode' rather than 'car as passenger'.
- The car to cycle estimate of 25% is within the range of estimates identified for the Danish cycle superhighways of between 9% and 26% (Cycle Superhighway 2019), and within the range reported for infrastructure interventions implemented in Los Angeles of between 13% and 33% (Matute et al. 2016).
- The CCA weighted mean estimates for car to cycle are lower than (about a third of) those drawn from the NTS modelling estimates that have been examined by Lovelace et al. (2011) and Sloman et al. (2019).

Overall, there is no reason, from this assessment, to suspect that a central estimate of 25% for the diversion of car trips to cycle trips resulting from an investment in infrastructure is atypical.

Normalising the weighted mean diversion factors

The weighted mean marginal diversion factors shown in the Table 17 sum to 104% rather than 100%. This is because the weighted means are estimated independently for each 'transfer from' mode, averaging across the CCA surveys and are not mathematically constrained to sum to 100%.

To estimate how new cycling trips breakdown by 'transfer from' mode as is required in intervention appraisals, it is necessary for the diversion factors for the available choice set to be *normalised* to sum to 100%. If the non-normalised factors were applied, then the number of trips disaggregated by 'transfer from' mode would not add up to the number of predicted new cycling trips (the total would be 4% higher). In this case, normalising involves multiplying all diversion factors by a factor of

(100% / 104%), as shown in the 'Normalised marginal diversion factors' column of Table 18.

Table 18: Normalised weighted mean marginal cycling diversion factors for infrastructure interventions

Transfer from mode	Weighted mean marginal diversion factor	95% confidence Interval	Normalised marginal diversion factors
Would use car (as driver or pass)	25%	22%-28%	24%
Would use other modes	55%	51%-58%	53%
Would not make this journey	24%	20%-28%	23%
Sum	104%		100%

Options for including revised diversion factors in TAG

There are two options for incorporating the evidence presented in Table 18 in the TAG databook:

- Option 1: Entirely replace the existing TAG diversion factors with the revised values presented in Table 18 (column titled "Normalised marginal diversion factors"). This will mean reducing the number of 'transfer from' transport modes available in the diversion factor choice set presented in TAG.
- Option 2: Re-normalise the existing TAG diversion factors so that they match the revised normalised values. These values are shown in Table 19 (column titled "TAG Metropolitan re-normalised to match CCA estimates"), with details on how these values are calculated provided below. This option retains the level of modal disaggregation currently presented in TAG.

The first option - entirely replacing the existing TAG diversion factors with the normalised values presented in Table 18 – has the following strengths: (i) most decongestion and environmental benefits of proposed cycling interventions will accrue from modal transfer to cycle from car. This present analysis has provided a reasonable central estimate of a car to cycle diversion factor, based on recent evidence in England linked to infrastructure interventions; (ii) The values in Table 18 provide a truer representation of the extent of the UK evidence base compared to the current TAG values which are also drawn from international studies; and (iii) The coarser level of modal disaggregation provided by Table 18 places a desirable requirement on analysts to generate and draw on more detailed evidence for their local contexts, where possible given evidence availability and local authority capacity. This is desirable because diversion factors will vary by area (as is demonstrated by the CCA RUIS diversion factors) and in response to different forms of intervention. The absence of a finer level modal disaggregation is a notable limitation, however. For example, the absence of a diversion factor for taxi could potentially lead to an under-estimate of the decongestion benefits associated with transfers from car based journeys to cycling.

The second option is to re-normalise the existing TAG diversion factors so that they match the normalised values presented in Table 18. The process of renormalizing is as follows:

- The current TAG 11% car to cycle diversion factor is replaced with 24% from the revised estimates;
- The current 17% ‘no travel’ diversion factor is replaced with 23% from the revised estimates.
- The diversion factors for other modes are factored so that they sum to 53% (from the revised estimates) rather than 72% by applying a factor of 53 / 72.

(Note that the current TAG factors have already been normalised, hence the use of the term re-normalising).

This approach has benefits because the finer level modal disaggregation is retained. There are risks however: The revised diversion factor values for non-car modes have not been verified by the available evidence. The table could be misinterpreted as suggesting that precise and highly disaggregated predictions can be made by applying these figures at face value, when in fact the evidence base is limited. To address this issue, uncertainty in the figures can be made explicit to analysts and it can be recommended that value for money assessments are subject to sensitivity tests; for example, by evaluating low and high car to cycle modal transfer scenarios.

Table 19: TAG diversion factors re-normalised to match weighted mean diversion factors

Recipient/source mode	TAG Metropolitan diversion factors	Normalised weighted averages from CCA RUIS	TAG Metropolitan re-normalised to match CCA estimates
Car	11%	24%	24%
Taxi	8%		6%
Bus	19%		14%
Rail	14%		10%
Light Rail	12%		9%
Walk	19%		14%
Subtotal non-car modes	**72%**	**53%**	**53%**
No Travel	17%	23%	23%

Recommendations summary

- It is concluded that the TAG car to cycle diversion factor ought to be revised to be in line with the normalised marginal diversion factors presented in Table 18.
- A judgement will need to be made as to whether the full disaggregation by mode is retained in TAG as presented in Table 19 (using the values in the column titled “TAG Metropolitan re-normalised to match CCA estimates”, following option 2), or replaced with the modal disaggregation presented in Table 18 (using the values in the column titled “Normalised marginal diversion factors”, following option 1).

Cycling diversion factors for non-infrastructure interventions

As noted previously, diversion factors will be expected to vary by intervention type. The review revealed insufficient evidence to enable meaningful typical estimates of diversion factors for non-infrastructure interventions to be derived. However, three case study examples which provided evidence of marginal diversion factors are re-presented in Table 20 – two of which relate to cycle hire schemes (London and Dublin) and one relates to the Bike-it maintenance programme delivered during the Covid-19 lockdown periods. It is not recommended that these diversion factors would be applied in scheme appraisals at face value as they are highly context dependent. However, they could be provided as look-up tables in TAG *for consideration as an indicative sense check* on bespoke figures derived by analysts.

Table 20: Example cycling diversion factors for non-infrastructure interventions

Source	Woodcock et al. (2014)	Murphy and Usher (2015)	Cycling UK (2021)
Intervention	London cycle hire	Dublin cycle hire	Cycle maintenance services
Comment	Car to cycle likely to be lower than other cities due to low baseline car mode share		Car to cycle diversion factor likely to be higher than typical as the intervention took place during Covid-19 lockdown periods
Car	2%	20%	38%
Taxi	3%	-	-
Bus	19%	26%	-
Train	2%	9%	-
Tram	-	-	-
Underground	29%	-	-
Motorcycle	1%	-	-
Walk	33%	46%	-
Other	1%	-	-
New trip	10%	-	-

Dealing with variation in conventional cycling diversion factors

Marginal cycling diversion factors in response to infrastructure and non-infrastructure interventions will vary, potentially quite significantly by context, and this should also be accounted for in how analysts derive and apply diversion factors in value for money calculations. Although further research is required to provide quantifiable evidence of the extent to which diversion factors vary in response to different conditions, the wider evidence base on travel behaviour suggests that cycling diversion factors will be influenced by:

1. **The baseline cycling mode share** – a low cycling mode share is likely to be linked to greater potential for modal shift to cycling and hence relatively higher marginal cycling diversion factors. Wardman et al's (2018) assessment of cross-elasticities of demand confirms that cross elasticities vary with baseline mode share. For example, a bus to car price elasticity is predicted to increase from 0.16

to 0.2 for commuting in urban areas where the ratio of car to bus market share increases from 4 to 7.

2. **Trip distance** – cycling diversion factors will reduce with increasing journey distance (all else being equal), probably in proportion to the relationship between journey distance and cycling mode share revealed by nationally representative data sets like National Travel Survey.
3. **Degree of urbanicity** – cycling diversion factors may be expected to be higher in urban areas (all else being equal) since trip distances reduce with degree of urbanicity.
4. **Journey purpose** – Nankivell's (2021) assessment of average cycling diversion factors in Greater Manchester revealed that diversion factors from car ranged between 19% for education trips to 44% for business trips. The range may be related to the baseline mode share for different journey purposes (i.e. education trips may have a lower car mode share, and hence lower potential for car trips to switch to cycling) and to the opportunities and constraints presented by different journey purposes (e.g. constraints relating to time, distance, the need to carry luggage, the ability to deal with physical activity / weather conditions).
5. **Type of infrastructure and intervention type** – For example, Sloman et al. (2021) note that cycle infrastructure suited to leisure cycling (such as the canal side routes delivered in Birmingham) may generate more trips that would not otherwise have occurred on other forms of infrastructure and hence diversion factors from 'no travel' would be higher in such cases. At the extreme, localised interventions such as the removal of parking rights at workplaces could generate car to cycle diversion factors as high as 100% (e.g., where all new cyclists travelling to a workplace have transferred from car commuting).
6. **Cumulative impacts of cycling interventions -** a single short section of cycle lane is likely to have less effect on modal transfer than a fully integrated network of cycle lanes.
7. **Short and long run effects -** the long run modal transfer to cycling where cycling conditions are improved may be expected to be larger than short run modal transfer as people take time adapt to changes to the travel environment e.g., short run fuel price elasticities have been observed to be lower than long term fuel price elasticities. Dargay and Hanly (1999) recommend bus fare elasticities of -0.2 to -0.3 in the short run increasing to -0.7 to -0.9 in the long run.
8. **The spatial and transport planning context -** e.g., complimentary measures to manage down demand for car use (clean air zones for example) would be expected to increase cycling diversion factors.

The implication of this known variation and uncertainty in predictions made on the basis of mean diversion factor values (such as those presented in Table 18), is that analysts should be encouraged to not take guidance diversion factor values at face value. Indeed, it is good practice in value for money appraisals, to employ sensitivity tests on behaviour change estimates, to identify and interpret diversion factor thresholds (e.g. upper and lower limits on car to cycle diversion factors) beyond which value for money estimates change significantly.

3.4 Limitations and future requirements

The published evidence base on the specific issue of estimating cycling diversion factors in UK contexts appears very limited. There were indications from email communications and in some reports that further RUIS data sets exist (for example, held by transport authorities like Transport for London) but the results of diversion factor estimates were not reported. Likewise, some data sets generated by academic studies may enable the estimation of diversion factors, but this has not been a core focus of the research and hence diversion factors have not been reported in published papers.

The revised diversion factors for infrastructure interventions presented in Table 18 are based on the single evaluation of the seven cycle city ambition fund interventions (Sloman et al. (2021)). This has meant that it has not been possible to address all of the evidence limitations identified at the outset of the review. Indeed, there remains a need to develop the UK evidence base on the following:

1. cycling diversion factors outside cities;
2. how cycling diversion factors vary by baseline mode share and journey purpose;
3. how cycling diversion factors vary by trip length;
4. how cycling diversion factors disaggregate by 'transfer from' modes;
5. how cycling diversion factors vary by intervention type; and
6. how cycling diversion factors vary over the short and long run.

Observational surveys (such as RUISs) which capture behaviour of the same individuals before (retrospectively) and after scheme implementation are recommended as the most appropriate mechanism to measure marginal cycling diversion factors. Such surveys should be included in monitoring and evaluation plans. There are issues with RUISs that can be mitigated through good survey design, as follows:

1. Sample sizes need to be large such that a sufficiently large number of *new* (as opposed to re-routed) cycle trips are captured. The CCA RUIS demonstrated that the number of new cycle trips captured can be a small sub-sample of cyclists using a new piece of infrastructure. This reduces confidence in diversion factor estimates and restricts the ability to disaggregate by the full set of available 'transfer from' modes.
2. Knowledge of the characteristics of the population of cyclists in a local area is required to evaluate the extent to which RUIS samples are representative of this population.
3. RUIS require respondents to self-report and this may introduce inaccuracies. Results from self-reported surveys ought to be verified against objective indicators of changes in the volume of cycle traffic and general traffic.
4. It would be best practice to undertake RUIS at several time points following interventions to understand whether transfer to cycling has been maintained, increased, or reduced over the longer term.

It should be noted that diversion factors are a necessarily reductive representation of behaviour change to enable reasonable value for money estimates to be evaluated and compared across schemes. Diversion factors should not be viewed as offering potential to make very precise predictions of behaviour change. Travel behaviour change is a complex process and there is not a simple cause and effect relationship between interventions and immediate behaviour change.

4 Considerations for e-cycle diversion factors

E-cycles need to be treated separately in analyses of benefits associated with cycling interventions since the user and usage profiles of e-cycles are different to the user and usage profiles of conventional cycles. This is because e-cycles have longer ranges, require lower levels of physical exertion and are a new technology. Hence a separate, sub-review of evidence relating to modal transfer to e-cycles was performed as is summarised in the following sections.

4.1 Evidence search strategy

Evidence on e-cycles was identified firstly through an evaluation of recently published literature reviews led by UK based researchers and known to the project team (Bourne et al. (2020), Cairns et al. (2017), Melia and Bartle (2021), Shergold (2021), and Phillips et al. (2022)). UK based empirical studies of modal transfer to e-cycles linked to these literature reviews were then evaluated (Cairns et al. (2017), Melia and Bartle (2021), and Bikeplus (2016)).

Relevant and recent international empirical studies of modal transfer to e-cycles were identified using a snowballing approach from the literature review reference lists. Finally, a limited review of evidence on the use e-cargo cycles for freight was performed, drawing on two review studies known to the project team: Naryanan and Antoniou (2022), and Cairns and Sloman (2019).

4.2 Evidence review

The evidence on e-cycle diversion factors is summarised in four sections linked to the search strategy:

1. UK authored literature reviews;
2. UK studies of modal shift to e-cycles;
3. International studies of modal shift to e-cycles; and
4. Use of e-cargo cycles for freight movements.

UK authored literature reviews

Bourne et al. (2020) provide a review of published and unpublished international literature (76 sources) on 'the impact of e-cycling on travel behaviour'. Diversion factor ranges from conventional cycle, car and public transport are summarised in

Table 21. The review does not provide details on method or evidence quality, but it is notable that the diversion factor ranges are wide for all three ‘transfer from’ modes.

Table 21: E-cycle diversion factor ranges identified in Bourne et al. (2020)

Proportion of e-cycle trips previously conducted by:	Evidence range
Conventional cycle	23% to 72%
Car	20% to 86%
Public transport	3% to 45%
Source: Bourne et al. (2020). Ranges are drawn from an international literature review	

Bourne et al. (2020) identify that e-cycle diversion factors vary according to:

1. Demographic group: Diversion factors from conventional cycle are likely to be higher amongst older age groups e.g. Up to 72% of e-cycle trips had transferred from conventional bike among older adults based on a survey of older adults in Belgium (Van Cauwenberg et al. 2018).
2. City transport context: Diversion factors from car are likely to be higher in car oriented cities compared to public transport oriented cities, e.g. 34% of e-cycle trips transferred from conventional bike and 38% from private car in Antwerp compared to 22% transferring from public transport in Zurich) (Castro et al. 2019).
3. Degree of rurality: Diversion factors from car are likely to be higher in more rural areas e.g. Hiselius and Svensson (2017) reported, based on a study in Sweden, e-cycle diversion factors from car of between 71-86% in rural areas compared to between 42-60% in urban areas.

Cairns et al. (2017) summarise evidence from the literature of the impacts of e-cycle use on other modes. Diversion factors drawn from this review are summarised in Table 22. Car to e-cycle diversion factors vary greatly, ranging between 16-67% depending on location and intervention type.

Shergold (2021) provides a review of evidence on trials designed to enable people to try out e-cycles. The review summarised some evidence of mode shift in terms of changes in mode share, but direct evidence of e-cycle diversion factors is not identified or reported.

Table 22: E-cycle diversion factor ranges identified by Cairns et al. (2017)

Source	Percentage of e-cycle trips previously conducted by:	Range
Hiselius and Svenssona (2014) A survey of e-cycle purchasers in Sweden A range is reported because diversion factors for e-cycle journeys varied by journey purpose.	Walking Public Transport Conventional bike Car trip	3% -12% 4%-16% 15%-26% 47%-67%
Kairos (2010) Evaluation of subsidies of e-cycle purchases for 342 individuals and 93 organisations in Voralberg, Austria. 196 individuals provided data on e-cycle use	Conventional bike Car driver	52% 35%
Mobiel 21 A survey of 369 e-cycle commuters in Flanders, undertaken in spring 2014	Car commuter	46%
Hendriksen et al. (2008) A survey of 28 e-cycle commuters in the Netherlands. Note the sample is too small for the percentages to be meaningful.	Conventional bike Car Public transport Motorbike / scooter New trips	33% of 28 people 16% of 28 people 8% of 28 people 5% of 28 people 38% of 28 people
Wright (2013) Evaluation of 10 e-cycles deployed in Totnes neighbourhood community groups. Sample size is unknown and the report is no longer available online	Car	40%-70%
Helms et al. (2015) Data collected in 4 regions of Germany from 70 existing e-cycle users and 312 trial participants	Car Conventional bike Public transport Walking New trips Other modes	41% 38% 7% 4% 6% 5%
Notes: Figures drawn from Cairns et al. (2017)		

UK studies of modal shift to e-cycles

Melia and Bartle (2021) conducted an online survey of 2092 e-cycle users located in the UK in 2019. Respondents that reported commuting to work by e-cycles were asked ‘before you started commuting by e-cycle, what was your main commute mode?' The resulting e-cycle commuting diversion factors are summarised in Table 23, indicating a car to e-cycle diversion factor of 45%.

Table 23: E-cycle commuting diversion factors (Melia and Bartle, 2021)

Previous commute mode	Percentage	n
Conventional cycle	32%	147
Driving a car or van	45%	207
Other	23%	109
Total	100%	463
Source: Melia and Bartle 2021		

Cairns et al. (2017) evaluated the impact on travel behaviour of 35 e-cycles loaned to 80 employees working for employers based in Brighton. Diversion factors are not reported, but miles driven in the previous week amongst trial participants reduced from 54 miles on average to 43 miles on average – a reduction in weekly miles driven of 20%.

Bikeplus (2016) summarise findings from an evaluation of 11 shared e-cycle projects implemented in various locations in England. The evaluation included a survey of 470 users, which included a question on the mode of transport that would have been used for the journey if the e-cycle share system were not available. Diversion factors are summarised in Table 24. Overall, 46% of shared e-cycle journeys were previously made by car as passenger, driver or taxi:

Table 24: E-cycle share system diversion factors

Mode	Percentage of trips previously made by mode
Car driver	35%
Own bicycle	19%
Bus	16%
Walking	15%
Car passenger	6%
Taxi	4%
Train	4%
Car club car	1%
Total	**100%**
Source: Bikeplus (2016)	

Phillips et al. (2022) perform a modelling exercise to estimate the maximum potential for e-cycles to reduce carbon dioxide emissions in England. It is estimated that car kilometres per person could be reduced by up to 2,600 km per annum on average, if every adult in England had an e-cycle. This estimate is drawn from a simulation of a population of 43 million adults. Adults are assumed to have an upper capability of active travel of 2 hours a day and assumptions are made about physical exertion limits from which an attribute indicating distance able to be travelled by e-cycle each day is calculated.

International studies of modal shift to e-cycles

Berjisiam and Bigazzi (2019) observe that there is not much evidence to date on the extent of modal transfer after e-cycle adoption. They estimate average e-cycle diversion factors using data from eight studies (seven from Europe and one from the USA), as summarised in Table 25. The method used to derive these averages is not explained.

Table 25: Estimated mean e-cycle diversion factors from Berjisiam and Bigazzi (2019)

Mode	Percentage transfer to e-cycle	SD	Number of studies
Car	44%	17.3	8
Conventional bicycle	30%	12.7	7
Public transport	12%	5	6
Walking	6%	3	2
New trips (assumed to normalise to 100%)	8%	-	-
Total	**100%**		

Source: Berjisiam and Bigazzi (2019)
SD – Standard Deviation

Castro et al. (2019) report results from a longitudinal online travel behaviour survey conducted between November 2014 and January 2017, amongst people living in seven European cities: Antwerp (Belgium), Barcelona (Spain), London (United Kingdom), Orebro (Sweden), Rome (Italy), Vienna (Austria) and Zurich (Switzerland). The sample was not representative, and respondents were recruited 'opportunistically'. The survey captured 365 e-cycle users across the seven cities. The e-cycle users were asked to report what transport mode had been substituted by e-cycle. The resulting diversion factors, aggregated across all seven cities are summarised in Table 26.

Table 26: Estimated average E-cycle diversion factors from Castro et al. (2019)

Mode	Percentage transfer to e-cycle	CI min	CI max	n
Private car	25%	20%	31%	93
Public transport	15%	9%	20%	53
Conventional bicycle	23%	18%	28%	83
Other	1%	0%	7%	5
None	4%	0%	9%	14
Combination of modes	32%	27%	38%	117
Total	**100%**			**365**

Source: Castro et al. (2019)
CI – Confidence Interval

The diversion factors vary by city as summarised in Table 27 (note that the percentages are not meaningful in many cases, due to the low sample sizes when disaggregated by city). Diversion from private car ranged from 2% in Vienna to 38% in Antwerp and it is suggested that the baseline mode share in a city is likely to be an influencing factor.

Table 27: Estimated average e-cycle diversion factors, disaggregated by city (Castro et al. 2019)

		Percentage transfer to e-cycle from			
City	**n**	**Bicycle**	**Public Transport**	**Private car**	**Other**
Antwerp	112	34%	7%	38%	21%
Barcelona	20	15%	35%	25%	25%
London	5	60%	0%	0%	40%
Orebro	18	22%	6%	17%	56%
Rome	63	5%	13%	49%	33%
Vienna	40	30%	12%	2%	55%
Zurich	107	19%	22%	10%	49%
Total	**365**				

Source: Castro et al. (2019)

De Kruijf et al. (2018) evaluate an e-cycle commuting incentive programme that was introduced in the North-Brabant province of the Netherlands. To take part in the incentive programme, participants had to undertake 50% of their commute trips by car, have a commute distance of 3km or over and be aged between 18 and 65. Participants received €0.15 per kilometre e-cycled in the peak period (€0.08 in the off peak), earning up to a maximum of €1,000 over the year. Travel behaviour was measured at three time points (one time point before the programme and two time points during the programme) and the survey returned 547 responses.

Diversion factors are not reported, but the survey revealed that car commute mode share (calculated as the proportion of distance travelled by each mode) reduced from 62% to 28% at the same time as e-cycle commute mode share increasing from 0 to 68% (Table 28).

Table 28: Commute mode share before and during e-cycle incentive programme (De Kruijf et al. 2018)

	Percentage of distance commuted by mode		
Mode	**Before e-cycle incentive programme**	**During programme time point 1**	**During programme time point 2**
Car	62%	28%	24%
Bike	33%	1%	1%
E-cycle	0%	68%	73%
Other	5%	3%	2%
Total	**100%**	**100%**	**100%**

Source: De Kruijf et al. (2018)

Hiselius and Svensson (2017) report diversion factors from an online survey of e-cycle owners in Sweden. Questionnaires were sent in May 2013, to 1300 e-cycle owners listed in an e-cycle retailer's customer database, generating a return of 321 responses. E-cycle diversion factors, disaggregated by journey purpose and by urban / rural location are summarised in Table 29, revealing the extent to which e-cycle diversion factors from car are higher in rural areas than they are in urban areas.

Table 29: E-cycle diversion factors disaggregated by urban / rural and journey purpose (Hiselius and Svenusson 2017)

		Journey purpose					
		Work	**Food shopping**	**Other shopping**	**Visiting friends**	**Leisure**	**n**
Urban	%age of respondents using an e-cycle	66%	55%	60%	58%	44%	460
	Conventional bike	27%	29%	19%	23%	37%	
	Public Transport	21%	11%	21%	24%	21%	
	Car	52%	60%	59%	52%	42%	
Rural	%age of respondents using an e-cycle	52%	61%	54%	27%	52%	426
	Conventional bike	11%	14%	13%	14%	26%	
	Public Transport	14%	0%	4%	3%	3%	
	Car	75%	86%	83%	83%	71%	

Source: Hiselius and Svensson (2017)

Macarthur et al. (2018) report results from an online survey, administered from April to July 2017, of 1,796 e-cycle owners and /or regular e-cycle users, living in north America (i.e. US – n=1,663 and Canada – n= 133). The sample is not representative - survey respondents were recruited via several promotional activities including social media, and promotion via retailers. Respondents were asked to report the mode of transport they would have used for their most recent three e-cycle trips as an alternative to the e-cycle. The resultant diversion factors are summarised in Table 30, indicating a car to e-cycle diversion factor of 46% when aggregated across all journey purposes.

Table 30: E-cycle diversion factors disaggregated by journey purpose (Macarthur et al. 2018)

	Conventional bike, walk, public transport or bike share	Car	Would not have travelled	Other	Total	n
All journey purposes	**27%**	**46%**	**25%**	**2%**	**100%**	**3894**
Commute (work of school)	33%	64%	1%	2%	100%	1273
Entertainment	30%	56%	12%	1%	100%	283
Recreation of exercise	23%	12%	63%	2%	100%	1388
Personal errands	26%	69%	4%	1%	100%	774
Visit friends / family	24%	65%	10%	1%	100%	135
Other	20%	34%	36%	10%	100%	42
n	**1063**	**1776**	**986**	**69**		
Mileage / Trip	9.4	9.3	14.3	11.3		

Source: Macarthur et al. (2018)

Sun et al. (2020) analyse data from the Dutch Mobility Panel survey (members of the same 2,500 households complete a three-day travel diary every year). 107 new e-cycle owners are identified over a four year period (2013 to 2016). The mode share for e-cycle adopters, calculated by journey distance (as this is more salient than mode share by number of trips when considering carbon savings) is compared before and after adoption of an e-cycle. The changes in mode share after adopting an e-cycle are summarised by journey distance band in Table 31 and by journey purpose in Table 32. This shows, for example, that car mode share for journeys less than 5 km reduces from 34% to 28% after e-cycle adoption. Diversion factors are not reported however.

Table 31: Change in mode share before and after e-cycle adoption, by trip distance

	Car		Conventional bike		E-cycle		Walking		PT&Other		Number of trips	
Trip distance (km)	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**
<5	33.6%	27.6%	40.3%	6.9%		47.6%	23%	16.4%	3%	1.4%	699	720
5-10	77.8%	54.9%	7.8%	1.3%		41.2%	3.6%	0.7%	10.8%	2%	167	153
10-15	81.3%	57.3%	4.2%	0%		33.3%	2.1%	1.3%	12.5%	8%	48	75
15-20	67.6%	63.4%	10.8%	0%		36.6%	0%	0%	21.6%	0%	37	41
>20	77.5%	72.6%	2.7%	0%		13.7%	0%	0%	19.8%	13.7%	111	95

Source: Sun et al. (2020)
B – Mode share before e-cycle adoption
A – Mode share after e-cycle adoption

Table 32: Change in mode share before and after e-cycle adoption, by journey purpose

	Car		Conventional bike		E-cycle		Walking		PT&Other		Total (km)	
Journey purpose	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**
Commuting	76.3%	50.8%	9%	0.1%		37.6%	0.1%	0%	14.7%	11.4%	1734.13	2151.83
Shopping	67.8%	50.6%	13.5%	2.1%		41%	2.6%	1%	16.2%	5.3%	1406.46	1265.54
Leisure	66.8%	69.8%	8.7%	0.8%		12.3%	4.6%	2.1%	19.9%	15%	3462.99	4414.07
Transport	86.7%	82.7%	6%	1.5%		15.3%	1%	0.5%	6.4%	0%	1721	698.51
Other and unknown	82.1%	66.5%	3.2%	4.1%		20%	0.7%	3.1%	14%	6.3%	1598.7	393.95

Source: Sun et al. (2020)
B – Mode share before e-cycle adoption
A – Mode share after e-cycle adoption

Use of e-cargo cycles for freight movements

Analyses of the mode shift potential of e-cargo cycles for goods deliveries focus on estimating the proportion of motorised vehicles that could credibly be replaced by e-cargo cycles (e.g. Naryanan and Antoniou 2021, Cairns and Sloman, 2019).

Cairns and Sloman (2019) review two European studies (The CycleLogistics project and the LEFV-LOGIC project) which indicated that between 10%-30% of “trips made by delivery / service companies [in cities] may have the potential to be replaced by (e-) cargo cycles”. Naryanan and Antoniou (2021) carry out a review of electric cargo cycles and identify studies estimating potential vehicle substitution percentages ranging between 10% and 83% depending on context and delivery type (Table 33).

Table 33: Estimates of potential e-cargo cycle freight vehicle substitution percentages

Study	Potential for e-cargo bikes to substitute for other vehicles	Author comment
Gruber et al. (2013)	66-83%	Of direct courier deliveries
Lenz and Riehle (2013)	25%	Of all freight transport at city centre
Koning and Conway (2016)	63%	Actual e-cargo penetration of total cycle freight (103 tkm/day in 2001 vs 1107 tkm/day in 2014. Paris Study.
Wrighton and Reiter (2016)	17%	Based on Cyclelogistics project measuring shift from car trips
Melo and Baptista (2017)	10%	Freight transport in areas with maximum linear distance of 2km

Source: Naryanan and Antoniou (2021)

It may be reasonably assumed that all e-cargo cycle freight trips have substituted for a motorised mode - a diversion factor of 100%. With respect to understanding substitution effects of e-cargo cycle freight trips for the purposes of estimating, for example carbon savings from a single e-cargo cycle freight trip, the salient questions to ask are:

1. What forms of delivery vehicle tend to be replaced by e-cargo cycle? and

2. How many e-cargo cycle journeys are required to replace a single delivery vehicle journey?

Konning and Conway (2016) surveyed 9 bicycle delivery companies based in Paris and found that e-cargo cycle were mainly replacing motorcycle and van deliveries, rather than larger goods vehicles.

New York City Department of Transport (2021) initiated an e-cargo bike trial with six participating delivery companies using 350 cargo bikes from April 2019. This demonstrated that e-cargo cycles can replace box trucks or vans on ratios of two e-cargo cycles to one van or even one e-cargo cycle to one van.

4.3 Summary

E-cycles are a new technology compared to conventional cycles and it is not currently possible to provide clear evidence based recommendations on e-cycle diversion factors. The adoption of e-cycles remains at an early stage and evidence on mode shift to e-cycles will change over time as e-cycle ownership and use increases.

Nevertheless the international evidence identified through the review indicates that car to e-cycle diversion factors can be expected to be higher than car to conventional cycle diversion factors. The studies summarised in Table 34 show diversion factors from car to e-cycle ranging between 25% to 46%, with an indicative mean value of 40%. This compares to the 25% marginal diversion factor estimated for conventional cycles. An important distinction to make however, is that these e-cycle diversion factors are in response to the acquisition of an e-cycle rather than a cycling intervention and in this sense they may be treated as average rather than marginal diversion factors.

Table 34: Summary of car to e-cycle diversion factors

Study	Journey purpose	Location	Sample size	Number from car	%age from car	CI lower limit	CI Upper limit	SE
Melia and Bartle (2021)	Commuting	UK	463	207	45%	40%	49%	2%
Castro et al. (2019)	Any journey	Pan-European	365	93	25%	21%	30%	2%
McArthur et al. (2017)	All journeys	North America	3894	1776	46%	44%	47%	1%
Berjism and Bigazzi (2019)	Any journey	Average over multiple studies			44%			
				Mean	**40%**			

CI – Condifdence Interval

Overall, there is a need for further research to inform how the uptake of e-cycles should be considered in scheme appraisal. Specifically there is a need for evidence on:

1. How e-cycle ownership is changing over time and how this is distributed across population groups;
2. How e-cycle use is changing over time, how e-cycles substitute for other modes, and how e-cycle mode share varies by trip distance; and
3. How e-cycle owners respond to interventions designed to increase cycling, such that marginal e-cycle diversion factors may be estimated.

Road user intercept surveys could be used to address the third of these questions and to estimate marginal e-cycle diversion factors, in the same way as for conventional cycle diversion factors. Indeed, it is recommended that all road user intercept surveys should include measures of cycle type so to enable disaggregation by conventional cycle / e-cycle. An issue at the current time, however, is that the numbers of e-cycle users using new infrastructure may still be small, making it difficult to generate sufficient sample sizes to enable the estimation of marginal e-cycle diversion factors.

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