TrafRed Model Specification

Authors: Paul Haggar, Research Associate, Cardiff University
Crispin Cooper, Lecturer, Cardiff University

Date: 17th April 2023

Doc Version: 1.0

Model Version: 3

Contents

1 Introduction

The aims of the TrafRed model are

- to provide a rough, back-of-the-envelope calculation to assist in developing Local Transport Plans that reduce the number of car miles driven
- to help inform discussion within and outside the Department for Transport of how the Transport Decarbonisation Plan might be strengthened
- to provide a proof of concept for a new kind of National Transport Model geared towards informing policies for decarbonization

To the greatest extent possible, we simulate the effects of a wide variety of “policy levers” on car miles travelled. These are simulated through elasticities of demand derived from the academic literature for the most part (e.g. for any changes relating to costs of car, bus or rail).

However in some cases (e.g. e-bike uptake, car occupancy increase) there is no strong evidence base for the extent to which these behaviours can be encouraged through policy. In these instances, we implement, instead, a “top-down assumption” parameter, allowing the user to specify the degree of uptake, but remain agnostic of how that uptake might be achieved.

It is important to note that TrafRed is an economic model and not a transport network model. Modal splits are based on national averages of mode share for each trip length, and trip lengths are based, in turn, on national averages for each urban/rural category. So, for example, in local authorities with limited rail service, the TrafRed model will overestimate the potential for railway use, as it is based on a national average and is agnostic of local rail network availability. The cost model is also quite basic, and does not include cost implications of services exceeding capacity. For more details see section 4.13.

As noted above, TrafRed can also be seen as a proof of concept. We have developed the model through an agile process approach, which alternated development sprints with feedback from our stakeholder group affiliated with Green Alliance. The first public iteration of the model (version 3) is therefore useful in itself as a record of the features considered most useful by stakeholders. We suggest, however, that our model limitations (section 6) are addressed in the event that the features scoped here are incorporated into any future national transport model.

2 Model overview

Starting with a baseline table of trips split by purpose, length, urban/rural classification and mode, we:

1. Apply uplift/elasticity and diversion factor models:
    a. Car club uptake (percentage reduction in car miles for members)
    b. Integrated transport uplift (percentage increase on bus and rail)
    c. Elasticities:
        i. car miles affected by price per mile (cost per mile plus amortized parking costs and congestion charge per trip pair) and car journey time
        ii. bus miles affected by ticket price, speed and frequency
        iii. rail miles affected by ticket price and frequency
    d. Bicycle uplift (as a multiplier)
    e. Diversion factors to estimate impact on other modes for all above changes
2. Apply specific modal interactions for which general diversion factors are not appropriate:
    a. Car occupancy increase: moves miles from Car driver to Car passenger
    b. E-bike uptake: transfers percentage of distance from all short motorized trips to bicycle
    c. Teleworking: reduces commuting to companies allowing work from home
3. Compute costs and revenue

3 Baseline

The baseline year is chosen as 2019 in order to capture pre-pandemic travel norms.

The baseline matrix for any local authority is constructed as follows:

1. Urban/Rural mixture for each Local Authority is sourced from ONS KS101EW - Usual resident population; with columns aggregated to match the categories of the National Travel Survey (Urban Conurbation, Urban City and Town, Rural Town and Fringe, Rural Village Hamlet and Isolated Dwelling). Further rows are added to the table to represent combined authorities.
2. Multiply urban/rural population mixture by NTS9907 (distance per person by urban/rural category) to get total distance by trip purpose and urban/rural category
3. Multiply (1) by NTSQ01008 (Average miles travelled by mode, region and Rural-Urban Classification of residence and trip length: England) to get distance bands for each rural category and purpose (not split by mode as NTSQ01008 does not include public transport modes)
4. Multiply (2) by NTS0308 (Average number of trips and distance travelled by trip length and main mode, England) to get modal split per purpose, rural/urban category and trip length.

Thus,

- The total distance for each trip purpose is determined by rural category
- The distribution of trip lengths is determined by rural category
- Baseline mode demand is determined by trip length.

But,

- Trip length is not affected by trip purpose
- Modal split is not affected by rural category, except indirectly via trip length.

Incorporating these relationships would be a potential future upgrade to the model.

4 Submodels

This section outlines the model for each policy lever or top-down assumption, in the order of application in the overall model (see section 0).

4.1 Car Club

4.1.1 Assumptions

Car clubs provide short-term rental from a fleet of vehicles often located at certain locations within a city. Car clubs are facilitated by innovations in digital service technology that automate this process. CoMoUk is a charity that accredits these services. Their 2021 report lists the main car club operators in the UK as ”Zipcar, Enterprise Car Club, Ubeeqo, Co Wheels, Co Cars and the car club subsection of Hiyacar” (CoMoUK 2022a). The DfT, supplied with CoMoUk statistics, provides a useful summary report for the UK (Department for Transport 2022a).

According to CoMoUk (CoMoUK 2022b), there were 297,172 active car-club users in the UK in March 2022 (used the service at least once in 12-months). The total membership is 784,870, but it stands to reason that inactive members won't be reducing their car-travel due to (or while) using the service. In the long run, most people can potentially learn to drive a car, so the population of the UK who can legally learn to drive, and are 16 years or older (Government Digital Service 2023), are potential users of car clubs in the long run, though there will be a subgroup who cannot drive due, for instance, to their age, health, or legal sanction.

Literature we have reviewed indicates that car-club use has a variety of motivations that could be described in an economic model, but not without some difficulty. Therefore, for brevity, we have assumed that the average reduction in car-use with the adoption of a car-club membership reflects a stable set of underlying motivations that is unknown but is consistent. Some potential motivations include: (1) lifestyle/identity motivations, or preferences; (2) cost reduction through the disaggregation of car products from a car-ownership bundle (e.g., particular-trips, one-way trips, extra household car-access). A second (and perhaps more important) assumption is that the car club supply can meet increased demand for these services in the long run. Through a complex socio-technological transition, automobiles became the dominant mode of transportation, and it is worthwhile to consider whether car-clubs could become dominant in the same way when the strong forces driving larger structural and social changes may be absent (Geels 2019). A third assumption is that this model assumes that the important practical question of how car-clubs are incentivized or encouraged has been addressed effectively; we have assumed that this is a model of what would happen to car travel if some incentive created a percentage change in the membership of car-clubs without identifying the means of this change.

Within the context of the TrafRed model, car club uptake is therefore implemented as a top-down assumption.

4.1.2 Empirical Change in Car-demand with Car-Club Membership

In evaluating the available evidence, perhaps the most important consideration is how these studies of relatively early adoption might differ from more extensive late adoption. Some studies that involve comparisons between changes in car-demand by trial members and existing members show large differences in the extent of reductions. This may reflect a trend for late adopters to make fewer reductions in their car-use and, hence, that car-use reductions would decline marginally as early adopters seeking to reduce car-use give way to late adopters taking advantage of the convenience or cost-saving aspects of the service. Another possibility to consider is that early adopters may drift back to habitual car-use in the long-run.

Car clubs are better developed in North America, and Shaheen et al. (Shaheen, Mallery, and Kingsley 2012) summarised the North American evidence available a decade previously. Ten studies having assessed changes in driven distance. These are (average change in VMT/VKT of members as %): -33, -45.5, -43, -79.8, -37, -42, -40, -60, -30.5, and -7.6. (Where separate outcomes are given for existing members and trial members, I've taken the average.) Further percentages are taken from later individual studies and from later evidence reviews, though none a focused systematic review on this topic.

- -28 and –45, Brussels and Bremen (Nijland and van Meerkerk 2017)
- -44, different US locations (Kent 2014)
- -27, different US locations (Kent 2014)
- -18.9, Netherlands (Nijland and van Meerkerk 2017)
- -7.2, Calgary, Canada (Amatuni et al. 2020))
- -18, UK (CoMoUK 2019)

Taking the average of these percentages gives -35%**.**

4.2 Integrated Transport

Integrated Transport System (ITS) can reflect several different elements. It's also something that has a long history of debate in the UK, with the UK Commission for Integrated Transport (CFIT) researching this for ten years (1999 to 2010), and more recently this being the subject of a 2018 report by the Campaign for Better Transport (Department for Transport 2010; Campaign for Better Transport 2018). Santos and colleagues (Santos, Behrendt, and Teytelboym 2010), section 2.1.1., include reference to a CFIT report in their outline of integrated transport as an intervention; this report still exists as an archived webpage (UK Commission for Integrated Transport 2007) and provides a basic (but outdated) introduction to the variety of concepts involved. Concerning the concept of ITS, Potter and Skinner were critical of the term as a political shibboleth (Potter and Skinner 2000; Potter 2010), offering more basic concepts to describe different policy elements that 'transport integration' could encompass:

1. *Functional Integration*. Joint ticketing across transport modes.
2. *Modal Integration.* Physical proximity between PT stops/stations and coordinated timetables.
3. *Information Integration.* A single information source (or seamless blending of multiple sources).
4. *Service Design Integration.* Openness of legal/administrative/governance structures to integration, e.g., market-led competition.
5. *Transport and Planning Integration.* Blending of the urban-planning regime to facilitate integration (e.g., zoning commerce in areas with good PT infrastructure; Netherlands' 'ABC' system is cited).
6. *Social Integration*. Involving a variety of stakeholders in transport policy, including others (e.g., businesses) with their own transport policies (e.g., for sustainable travel).

In this report, we focused on an aspect that was specific, contemporary, and that could reduce VMT if introduced widely, which was the functional integration or joint ticketing.

Before considering the potential of functional integration, it is important to try to benchmark how integrated (or unintegrated) UK transport is at present, compared to how it could be in the future. Turner and Wilson raise the (then) new issues of outside functional integration through integrated bank payments and digital services (Turner and Wilson 2010): transport operators beyond London had begun to functionally integrate through 'tap' payments from bank cards and ticket-selling apps rather than through an Oyster card roll-out discussed at the time - through a national ITSO standard that all operators could utilise (ITSO 2023). Campos Ferreira et al., in a book chapter about these technologies, suggest *de facto* functional integration taking place through 'mobile ticketing services' ("the use of a mobile device to purchase and/or validate a travel ticket or to initiate a journey"), with a lack of service design integration being due to "a complex, system-interdependent ecosystem of players whose success depends on the joint action of all players simultaneously" (Campos Ferreira, Galvão Dias, and Falcão e Cunha 2020). .

Evidence concerning integration through a smart card (e.g., Oyster-card) is older and so difficult to evaluate with respect to current transportation. Blythe briefly reports several prior experiments with smartcards undertaken in the 1990s in the UK, in Milton Keynes, Merseyside, Harrow, and Hertfordshire, as well as a list of early smart cards adopted by regional transport operators (Blythe 2004). In terms of evidence from the Oyster card itself, the Oyster card was introduced alongside a series of other important public transport improvements so, although there is evidence of a large increase in public transport satisfaction at that time, it cannot be unequivocally attributed to this one change in particular, and nor can any subsequent changes in ridership (Transport for London 2014). Similarly, the different elements (e.g., joined-up ticketing) seem to have been introduced before the card itself (Potter 2010). London congestion charging was introduced just 4-months before the Oyster card (Wikipedia 2023). The only research evidence we could identify of potential relevance, being not directly focused upon the effect of either Oyster cards or congestion charging, was difficult to evaluate (Prager et al. 2011). The What Works Centre (What Works Centre for Local Economic Growth 2016) also reports an absence of empirical evidence on this topic and, Audouin and Finger provide some background information (Audouin and Finger 2019).

We consulted current academic and non-academic sources relating to current and potential functional integration and transport integration more generally. The 2018 report *Integrated transport A new generation of interchanges* by the Campaign for Better Transport argues, broadly, for the following changes to stimulate transport integration: (a) planning reform (hence a call for transport and planning integration, as listed above); (b) investment and oversite of investment; (c) regional devolution of transportation. Hence, importantly, functional integration was not the focus of this report.[1] A 2016 report on integrated ticketing (What Works Centre for Local Economic Growth 2016) provides a review of research evidence concerning the effects of integrated ticketing (i.e., electronic rather than paper

[1] (i) The report states that "concepts like MaaS and associated progress with real-time information, smart ticketing and ride-hailing operations increasingly allow travellers to follow flexible itineraries, making swapping between modes and routes much easier and more commonplace"; (ii) an extension of Oyster card zoning into Thurrock (Essex) is briefly recommended; (iii) joint rail-bus ticketing for a express Cambridge-Rugby bus service is recommended; (iv) that devolution of powers to Cornwall has resulted in a smartphone journey planner introduced for the region. In short, a general statement, a few instances, and no evidence.

ticketing) on ridership. They identified five relevant published studies. Using this as our starting point, we considered these five studies, and also four studies undertaken after this review. We have summarised these below briefly.

> Abrate et al. used 12-year panel data from 69 Italian public transport providers, some with and some without integrated tariff systems, to study the impact of tariff systems on demand (ridership) from 1991 to 2002 (Abrate, Piacenza, and Vannoni 2009). Importantly, the integrated tariff system described was a ticket allowing use of all public transport within that area for a specific period (hours, the day, season-ticket) rather than a pre-payment card or smartphone mediated card or payment. Their statistical model indicated that integration increased ridership by 2.19% in the short-run and 12.04% in the long-run. Larger effects (short run, 5%, to long run, 30%, for each of three effects) were estimated when qualifying effects were considered, such as whether the ticket was urban or inter-urban and specific features of the tariff (single ticket, flexible zone access, extension of integrated area beyond the city or route). Hence, the effectiveness an integrated tariff was less effective when aspects of the tariff were allowed to vary.
>
> FitzRoy and Smith considered the Swiss cities of Basel, Bern, Geneva, and Zurich, with respect to ridership and the introduction of season tickets that were transferable across public transport modes, introduced in 1984, and in Geneca in 1987 (FitzRoy and Smith 1999). Comparing 1981 to 1991 ridership, public transport trips changed +29.9% (Basel), +61.0% (Bern), +67.6% (Geneva), and +34.8% (Zurich), with Geneva having fewer public transport trips per capita at the outset (187 compared to 487, 389 and 554, in Basel, Bern and Zurich). They used a pooled simple regression model (4 cities over 26 years) to investigate demand with and without these season tickets, while allowing for some other influential factors (e.g., price, income, service frequency). The estimated change in ridership due to season ticketing from this model was +4.5% in Basel, +14% in Bern, +16.1% in Geneva, and +5.4% in Zurich. It is worth noting that while Geneva is largely served by buses, the other three cities are largely served by trams, and trams are perhaps a less common means of public transport in UK cities.
>
> FitzRoy and Smith, previously (FitzRoy and Smith 1998), studied the success of public transport in Freiburg (its use more than doubled over about a decade), attributing this success to a similar 'environmental' travel card (again, introduced in 1984). Using OLS regressions over 27 years, allowing for some other influential factors, they estimated that an early version of the card increased ridership by 7% whereas a later version did so by 20%. In both studies (FitzRoy and Smith 1998; 1999), it is worth pointing out that the transport cards/season tickets were both comparatively cheap and had 'zero marginal financial cost' (no limits to travel for the duration of the ticket), and were applicable over a wide network and across different available modes.
>
> Matas studied the introduction of a similar travel pass in Madrid in 1986 (Matas 2004), using annual data from 1979 to 2001, and allowing for several other explanatory variables. Uplifts estimated were, in 1year/3years, +3.4%/+7.1% for bus ridership and +5.3%/+14.9% for underground ridership. Greater increases in underground ridership are attributable to other ongoing interventions (e.g., a network extension) not included in the statistical model. Later, Matas et al. did a similar study in Barcelona (Matas, Raymond, and Ruiz 2020), but modelling *mode-share* between public transport and automobile and using disaggregated survey data

from individuals (a relatively large travel survey from 2006). Analytically, rather than considering actual tickets, a general transportation model was created, and this was used to estimate the effects of ticket-type changes through price-subsidy impact. Four scenarios were investigated, of which two are relevant here: (a) extending the multi-modal flat-fare to a larger city area (zone) at current prices, (b) removing current multi-modal flat-fares in operation. The first scenario projected +4.2% in PT commuting and +4.7% in PT non-commuting (personal trips), the second reductions of 3.5% and 3.2%.

Alhassan et al. studied ridership with the introduction of integrated ticketing, ”Movingo“, in the Mälardalen region of Sweden (Alhassan et al. 2020). Their abstract reads: ”findings suggest that the scheme made rail commuting more attractive resulting in an overall increase of about 24% in ticket sales with 3% – 15% car commuters reporting that they patronised PT services after the project”. The 24% is from ’hard’ ticket-sales data. The 3%-15% is the confidence interval from a survey of motorists. Movingo was smartcard/mobile-phone based, and covered intra- and –inter city buses and all trains in the region, with coverage in some (or all) of the neighbouring regions also provided. Tickets covered durations of one-month, three-months or one year.

A further study (Gilbert and Jalilian 1991) was made of the introduction of similar passes in London in 1983 (bus-LRT), 1985 (LRT-British Rail) and 1989 (bus-LRT-British Rail). Unfortunately, the technical content of the article make it difficult to say with certainty that the elasticities they derive are applicable to the current project. A narrative/critical review exists on the topic of functional integration, though it’s focus is upon integration in MaaS (mobility as a service), rather than public transport, which limits its applicability, so we mention this only briefly (Kamargianni et al. 2016). Cited across several studies is an NEA Transport Research and Training report (Hilferink, Roest Crollius, and Van Elburg 2003) that considers around 8 European case studies of ticket integration, however we were unable to obtain a copy digitally. These studies seem to indicate the potential for substantial improvements in ridership, perhaps as much as 50%, with integrated ticketing, but the empirical evidence is, nevertheless, somewhat limited for a confident statement of an elasticity applicable across contexts.. For instance, time is a relevant issue: these studies are relatively old, and knowledge and technology in this area can develop rapidly. Several of these studies are presented as post-hoc investigations of successful public transport interventions, which raises the issue of selection bias: are similar ticketing systems that ‘failed’, or showed only modest success, not being investigated? Study-designs are also limited by the nature of the phenomenon (new ticketing is a one-off event that cannot be repeated, and is likely to occur alongside other service improvements, which can inflate estimates to the extent that they may have been overlooked or could not be measured.

On the basis of this evidence, we identified 14% as a long-run conservative estimate for our model. This is the median of the effects across the studies.

4.3 Car price

4.3.1 Assumptions and basic model

We began with several assumptions.

- Road price regimes affect driving cost per unit distance, and so are comparable to fuel costs.
- To the extent that traffic volumes fall, and driving times reduce, road price regimes can also encourage driving.

- Differences between long distance and short distance pricing regimes are reflected in differences between urban and extra-urban elasticities/contexts (because most long-distance driving is motorway driving)
- A road-price per km is a form of price elasticity similar to a fuel price in increasing the per-distance cost of driving.

We average the indicative elasticities given for fuel prices by Wardman in Table 7 (Wardman 2022b), and these are exactly the same as for unit-distance changes (all things being equal, a longer journey uses more fuel).

```
Car price elasticities:
Length over 10 miles:
  Commute -0.31
  Shop/Education -0.31
  Business -0.11
  Leisure -0.63
Length under 10 miles:
  Commute -0.16
  Shop/Education -0.16
  Business -0.1
  Leisure -0.33
```

We note that: (i) business elasticities are similar; (ii) other elasticities are double for inter-urban compared to urban travel; (iii) elasticities are greatest for leisure (i.e., people cut back on leisure trips first when driving becomes expensive); (iv) compared to other elasticities, fuel-price elasticities are relatively moderate – hence, time-elasticities of road-pricing are important, especially concerning potential rebound effects.

4.3.2 Parking charges

We take parking restriction policies to be effective, but this is not always the case. Local factors are important, particularly the relative 'cost' of parking in adjacent areas, or adjacent town-centres, and the availability of free (or illegally-free) parking. Hence, an effective policy is likely to take local factors into account.

There has been relatively little elasticity-based research on parking. Wardman's meta-analyses (Dunkerley et al. 2018; Wardman et al. 2018; Wardman 2022a; 2022b) sometimes consider parking cost: the own-price elasticities meta-analysis make a distinction between fuel and parking cost elasticities, noting no clear difference, perhaps due to the relatively fewer studies of parking cost demand price elasticity; hence, in this case, parking and fuel cost indicative elasticities are presumably synonymous. We have considered this in the assumptions, above. A meta-analysis of parking price elasticities puts the price elasticity of parking (tickets sold) at about -0.5, but this is more directly related to parking-price than car-use, hence not directly relevant (Lehner and Peer 2019).

4.3.3 Sense checking

We would expect the elasticities from Wardman's meta-model to be comparable to empirical findings. The empirical literature draws an important distinction between *urban road pricing* (usually done by entering/leaving a zone, or dwell-time in a zone) and *extra-urban road pricing* (e.g., toll motorways, which work, for example, by inbound/outbound cordons at exits). Some road pricing is geared simply to reduce traffic, whereas other road pricing is variable and aims to adjust pricing to match traffic levels, for instance across the day, and hence to make journey delays less likely.

Urban road pricing elasticities. In the studies we reviewed, distance travelled was almost never considered, perhaps as the necessary data is not usually available. Instead, elasticities concerned variables such as road-entry, road-volume and flow, in the aggregate, that can be broadly summarised as 'traffic'. One study (Croci 2016) reported the comparative elasticities of urban road pricing in three European cities: Stockholm (-0.70 to -0.85), Milan (-0.46 to -0.66) and London (-0.47). A study from Singapore (Olszewski & Xie, 2005) found the urban road price elasticity to vary with time of day from -0.082 to -0.324, however this was under a regime of regular price adjustment, and prior infrequent price adjustment events in the same system had given five elasticities of between –0.194 and –0.578 (-0.303 estimated overall in the long run). This mid-point average of these is -0.462.

Extra-urban elasticities. Likewise, distance travelled was almost never considered, and, instead, elasticities concerned variables reflecting road traffic. Gibson and Carnovale provide a summary of elasticity evidence across studies prior to 2015 (Gibson and Carnovale 2015). These range between –0.06 and –0.82. A mid-point average estimate across these studies is -0.243. Their own study, of road pricing in Milan, found a long-run price elasticity of -0.3. Croci cites several review studies that give indicative road tolling elasticities, at between -0.2 and –0.5, mid-point –0.35 (Croci 2016). Another article (Janson and Levinson 2014), treating high occupancy toll roads, summarises previous toll road elasticities, giving values between –0.03 and –0.82 (mid-point average 0.265). Matas and Raymond list studies with elasticities ranging between -0.03 and -0.5, mid-point average of -0.274 (Matas, A and Raymond, J. L. 2003); their own study reports average elasticities of between -0.33 and -1.31, depending on road-type. On this basis, the elasticities of pricing these roads are quite variable but seem to average to around -0.25.

We make the following observations. Urban road pricing seems more stable, but it may be just as variable as extra-urban road pricing with varying circumstances (Olszewski and Xie 2005). Another possibility is that the effect of road pricing on traffic varies with policy design – is the road price to reduce traffic 'full stop' (e.g., a congestion charge) or to regulate traffic (some prices vary according to time of day to spread the rush hour traffic). We have avoided pricing regimes that price road-speed, and high occupancy lane roads, as these introduce additional complications.

4.3.4 Estimation of scenario per-mile costs

For baseline costs per mile we take HMRC's figure of £0.19/mile for car usage, and allow this to increase as chosen by the user.

For congestion charges we assume a baseline of zero cost. Model users from London - with its £15 congestion charge - plus the 9 local authorities with clean air zones (most charging/will charge approx. £9) will have more recent data on traffic levels and can adapt predictions accordingly.

The model allows applying congestion charges to varying levels of rurality, e.g. with an option for rural towns as well as major conurbations. To determine the proportion of trips affected by such charges, because they start or end in a congestion charge zone, we have extracted a trip matrix aggregated to four rural/urban categories from Leeds ITS's NTEM2OD model (Morgan and Lovelace 2022).

Parking charges are applied to half of trips (i.e. assuming at-home parking is free at the time of use, or if paid for, that the road user considers this a fixed cost of vehicle ownership) with different charges applicable for parking away from home per trip purpose.

All per-trip costs are divided by trip length within each band to produce an amortized per-mile cost, which is used in the elasticity model.

4.4 Car journey time

4.4.1 Assumptions and basic model

This model assumes that the road journey-time change has already taken place (in reality, there are important dynamics as reductions in traffic encourage drivers back onto the roads). The model also assumes that the only distinctions between urban speed-limits (e.g., 20mph zones), i.e. zones where speed is controlled, and larger road speed limits (e.g., 55mph limit) are differences between urban and interurban time elasticities (in reality, the two are probably distinct contexts and so difficult to compare, and certainly have differing policy objectives).

Wardman gives own-time elasticities (km and trips) in Table 6 (Wardman 2022a). We average these to model increase in car journey time.

```
Car time elasticities:
Length over 10 miles:
  Commute -0.98
  Shop/Education -0.98
  Business -0.75
  Leisure -0.99
Length under 10 miles:
  Commute -0.79
  Shop/Education -0.79
  Business -0.6
  Leisure -0.8
```

4.4.2 Sense checking

Romero et al. found some evidence for speed-limit related traffic reductions from studying a policy in Madrid whereby traffic restrictions (highway speed-limits, zone-parking, zone car-access) were adjusted according to local air quality conditions in the city, with four different levels of restriction being implemented with worsening quality, and each level having a larger geographical coverage (Romero et al. 2019). This was not a study that reported elasticities, but they found that stage-one (which was just a reduction in highway speed limits) increased bus-use likelihood by 2%, subway use likelihood by about 6%, and reduced the use of toll highways (where the speeds were reduced) by 6%. The authors point to local car-dependency as a reason for the small-scale of these changes. More concretely, a study in Madrid (Perez-Prada and Monzon 2017), looking at emissions from traffic with a speed-limit reduction on the motorway ring-road (from 90kmph to 70 kmph, or about 56mph to 43mph), used traffic flows in the estimation methods, and they found that traffic volume (vehicle km) fell by 12.6% on speed-control area and by 3.5% across the whole ring-road; control areas (where speed limit was not implemented) were largely unchanged. For a 30% increase in journey time, our model shows a car reduction of about

10%. This is larger than the 3.5% in this study but the discrepancy could easily be explained by the fact that the ring road may only account for a fraction of in-vehicle time.

Nightingale et al. report the results of a policy of extending the 20mph speed limit zones in Edinburgh, UK, and report a very modest reduction in speed (around the 1-2mph level), however the study reports, but does not note, that the existing speeds in the city were already quite low (around 23.5mph, with a maximum of 32mph reported), indicating that potential for further reductions may have been limited (Nightingale et al. 2021). A study evaluating the implementation of a general speed-control policy in the Netherlands, with a 30kmph (18mph) speed limit (Vis, Dijkstra, and Slop 1992), reports traffic reductions of ”roughly” between 5% and 30%. Given the number of unknowns, we consider these figures to be in the same ballpark as our own model.

4.4.3 Impact of average speed for different road classes on car journey time

To take us a step closer to the policy levers that influence car journey time, we model the effect of reducing average speed on different road classes. This would likely be implemented via speed limits, with average speed being a function of speed limits, number of junctions (including e.g. traffic signal timings) and congestion. In the current model we are not able to include all of these factors, however we make use of average speed data collected by the Department for Transport.

- Strategic road network average speed 58.5mph; local A roads 23.8mph. (Note that the strategic network incorporates all motorways, whereas individual A roads may be classed either as local or strategic) (Department for Transport 2022b).
- Average time to access the strategic road network is 25 minutes, though can be over an hour for rural areas (e.g. Cornwall has average 87 minutes, and maximum 130 minutes). Given this range, we use 25 minutes for urban areas and 50 minutes for rural (Department for Transport 2014).
- We lack official data on average time to access a local A road, and speed on other local roads. Based on sampling a variety of route plans in Google Maps we estimate an average of 5 minutes at 13mph (in the absence of major congestion).

We note that the above-quoted times will change if average speeds change, and therefore convert them into average distances by assuming each trip using the strategic network must first access the local A road, then the strategic network:

*Average distance to local A road = average time to local A road * local road speed*

*Average distance to strategic road network = average distance to local A road + (average time to strategic net – average time to local A road) * local A road speed*

To compute the time for an individual trip of given distance, we then assume up to 5 trip stages

1. Compute time to cover
    a. distance from origin to local A road
    b. distance from local A road to destination

   at local speed (scale down as appropriate for shorter trips which do not reach A road)
2. Compute remaining trip distance unaccounted by step (1) (if any)
3. Compute time to cover
    a. distance from origin to strategic network, minus distance to local A road
    b. distance from strategic network to destination, minus distance to local A road

at local A road speed (scale down as appropriate if remaining trip distance is insufficient to reach strategic network)

4. Compute remaining trip distance unaccounted by step (3) (if any), and compute time to cover this distance at strategic network speed.

To compute average change in trip times for a given distance band and urban/rural category, we use (as in the congestion charge model) a trip matrix aggregated to four urban/rural categories from Leeds ITS's NTEM2OD model (Morgan and Lovelace 2022), to determine the likely mixture of destinations for trips originating in each urban/rural category. We make an exception for very short trips which we assume will all remain within the same urban/rural category; that is, trips under 5 miles from urban areas, and under 1 mile for rural towns.

4.5 Bus/Rail price

4.5.1 Assumptions and basic model

We assume a fare subsidy (not supply-side subsidy) proportional to distance, hence flat subsidy per mile.

We average elasticities from Wardman Table 7 (Wardman 2022b), taking urban elasticities to apply to trips under 10 miles, and rural elasticities to trips over 10 miles. We limit the maximum subsidy to 75% of ticket price as elasticities will not be suitable for modelling prices closer to zero.

```
Bus price elasticities:
 Length over 10 miles:
  Commute -0.63
  Shop/Education -0.63
  Business -0.63
  Leisure -0.91
 Length under 10 miles:
  Commute -0.44
  Shop/Education -0.63
  Business -0.63
  Leisure -0.51
Rail price elasticities:
 Length over 10 miles:
  Commute -0.81
  Shop/Education -0.81
  Business -0.70
  Leisure -1.12
 Length under 10 miles:
  Commute -0.68
  Shop/Education -0.68
  Business -0.66
  Leisure -1.29
```

4.5.2 Validation

In addition to the elasticity and diversion factor approach, we tested a cross-elasticity model based on Wardman et al., Table 8 (assuming 50th percentile of car:bus and car:rail relative mode shares Vc/Vb and Vc/Vr) (Wardman et al. 2018). Results are broadly similar to the diversion factor approach, for the range up to the maximum subsidy allowed in the model (75%). In order to simplify the combination of models we therefore use diversion factors common to several sub-models rather than cross-elasticities.

4.6 Bus speed

Wardman gives own-time elasticities (km and trips) in Table 6 (Wardman 2022a). We average these to model reductions in bus journey time.

```
Bus time elasticities:
Length under 10 miles:
  Commute -0.5
  Shop/Education -0.5
  Business -0.5
  Leisure -0.4
 Length over 10 miles:
  Commute -0.84
  Shop/Education -0.84
  Business -0.84
  Leisure -0.84
```

4.7 Bus/Rail frequency

Wardman's meta-analysis introduces the reader to the usual equation for generalised journey time (GJT) that links journey-time, headway, and number of interchanges, which is simply a linear model with coefficients on the latter two variables of which they write (section 1.2) "Fortunately for review purposes, these weights have essentially remained constant over the evidence here used and hence the estimated GJT elasticities are comparable" (Wardman 2022a). As such, we use headway elasticity of demand to represent bus and rail service frequency changes. (Headway is the distance or time between two moving vehicles, such as bus services; interchanges are the number of changes made between vehicles during a journey.)

The cross-price elasticity link to car-use change is complicated by the absence of a price change (i.e., generalised cost changes but not price). We therefore assume that the diversion factor is the best way to represent mode-switching, because this does not rely on quantifiable cost/price changes.

We average elasticities from Wardman Table 6 (Wardman 2022a).

```
Bus headway elasticities:
 Length under 10 miles:
  Commute -0.34
  Shop/Education -0.34
  Business -0.34
  Leisure -0.28
 Length over 10 miles:
  Commute -0.36
  Shop/Education -0.36
  Business -0.36
  Leisure -0.36
Rail headway elasticities:
 Length under 25 miles: -0.27
 Length over 25 miles: -0.18
```

Note: 'headway' is represented in the models as (i) an additional coefficient and (ii) some interaction coefficients for headway and some other factors, notably urban and inter-urban variables. It's important to note that using headway is a new addition/extension to the meta-analysis in 2022, and hence the meta-analysis used only 25 'studies' (i.e., elasticities from studies) to analyse the effect of headway, this is possibly why relatively few indicative elasticities are reported for headway (i.e., there are gaps in the evidence).

4.8 Improved Walking/Cycling Infrastructure

4.8.1 Evidence

The impact of building more infrastructure for physically active transport is a greater use of physically active transport (walking and cycling, primarily), but the envisioned impacts concern improvements in public health through physical fitness, environmental benefits through reductions in motorised travel, as well as ancillary benefits, such as creating safer communities and assisting the local economy (e.g., the 'high street'). Such a vision is outlined in a recent (2020) UK Department of Transport publication *Gear Change: A bold vision for cycling and walking* (Department for Transport and Active Travel England 2020). Similarly, the What Works Centre (What Works Centre for Local Economic Growth 2020) offered a cautious but broadly favourable assessment of such an approach for local economies and Transport For London present compelling statistics in their evidence packs (Transport for London 2023) including a specific presentation of positive evidence from the segregated cycling highways in London (Transport for London 2018). The primary emphasis in these sources is, however, economic, and not specific transportation or environment impacts. The effect of infrastructure upon active travel is a topic of interest that has generated much research. However, the nature of the phenomenon tends to limit the applicability of that research to car-use, and the effect on car-use is less well understood.

4.8.1.1 Changes in Cycling Infrastructure Usage

The studies we have cited here are relatively recent (thus they better reflect current infrastructural trends), but these articles also cite several older studies on this topic, which are also available; many are cited by van Goeverden et al., which is considered in detail below (van Goeverden et al. 2015). The range of effects is substantial, indicating the probability of important facilitation/barrier (qualifying) effects. However, the effects are generally positive and can be substantial. It is important to consider that these increases can be partly explained by cyclists altering their routes to incorporate new infrastructure, rather than reflecting only people increasing their cycling or switching their travel mode.

- A complication with active transport research is that some of the literature overlaps with health behaviour research, which is concerned with walking and cycling for health, but not necessarily for transportation alone. Mölenberg et al. systematically reviewed the literature on infrastructural interventions in the promotion of cycling, but, focusing on health, the overlap with physical activity that is not for transport is important to consider (Mölenberg et al. 2019). For effects of infrastructural interventions on changes in cycling *using the infrastructure* (21 outcomes), they found a range of increases between +4% and +438%, with median +62%, and for cycling *in general* (36 outcomes) a range between –21% and +262% with median +22%.
- Félix et al. collected observational data on the volume of cyclists using cycling infrastructure in Lisbon in 2016 (baseline), 2017 (after over 100km of dedicated (segregated) cycling infrastructure were added to the Central Business District (CBD), broadening it from a single central route to a network), and 2018 (after 1,400 shared-bicycles, 70% of them electric, were introduced to the area) (Félix, Cambra, and Moura 2020). It is worth mentioning that they used manual observations to collect data and that their 2016 baseline was collected during a prior study. Briefly: (a) between 2016 and 2017 three observation-points on the recently completed main cycling route through the CBD showed a 4- to 7-fold increase in cycling volume, whereas

observations made on a pre-existing cycling route and two routes without improvements showed few changes; (b) between 2017 and 2018, a 2.5-fold increase was observed on all routes with cycling infrastructure, but not on routes without infrastructure. The results of this study are clear and unequivocal, but several factors are worth considering. First, the article indicates that people in Lisbon were largely favourably disposed to improvements in cycling. Second, the climate in Lisbon could be more favourable to active travel than the climate in the UK (Hong, McArthur, and Livingston 2020). Thirdly, the authors indicate that while Lisbon is known for its hills, much of the city is basically flat terrain. Fourthly, the authors observe that the pre-existing conditions for cycling in the city were poor, and so left the necessary room for improvement. Finally, this study provides no information concerning modal shift or car-use.

- Similar research findings have recently been reported (Karpinski 2021). Shared-bicycle services have increased the use of bicycles in Boston, however this study shows that when segregated cycle infrastructure was introduced, an 80% increase in the use of shared-bicycles was found on these routes by comparison to routes without such infrastructure, amidst larger overall increases in cycling on all routes. Again, however, it is worth noting that many years of extensive effort had previously been made to make Boston a cycling friendly city, so it is possible that there existed a number of facilitating/enabling factors (much as in Lisbon, above).
- At least two studies consider the impacts of cycling infrastructure developed in Glasgow in the years before the 2014 Commonwealth Games it hosted, each using crowdsourcing data. Hong, Philip McArthur, *et al.* (2020) make use of data between 2013 and 2016 collected using the Strava application. The article reports a process of data-validation: observational data was closely correlated with app data over the same period. From a regression model of the app data, they report increases of between 12% and 18% in cycling with improved infrastructure, with three or four studied infrastructural improvements (i.e., cycling routes) showing these increases; one of the four routes, however, showed reductions in use - the authors note that this route (compared to the others) was over a longer distance, not close to the city-centre, connected to less population-dense areas, and was a route shared with other traffic (and so not segregated). The authors caution that the ”benefits of new infrastructure in outer areas could pay-off in the future when the network becomes more extensive, and people realise its existence as well as its usefulness as their normal travel option.” Using a similar approach and data, Hong and colleagues provide useful insights by considering, also, the effect of rain, finding that Glasgow’s rainy weather reduces cycling to a greater extent on safer routes (segregated, off-road) than normal on-road routes, which the authors attribute to safer routes being preferred by less experienced cyclists who are more likely to be discouraged by bad weather (ibid).
- Frank et al. report a natural experiment of the opening of a greenway in Vancouver, Canada; a ‘greenway’ is, here, a long road repurposed for active transportation including the addition of facilities for cyclists, safety features, and green-space (Frank, Hong, and Ngo 2021). They employed a mixed factorial natural experimental design with a comparison group residing at a greater distance from the infrastructure compared to the treatment group. Data was collected by survey, both in the months before the greenway opened and again around two-years after it opened. Their regression model estimated a +252% increase in cycling (trips) in the treatment compared to the comparison group. It is important to note that many factors were controlled in the regression, including car-share rates: the unadjusted difference between baseline and follow-up in the treatment group was +72.2% and marginally statistically significant. It was also

notable that the treatment group cycled less to begin with, and so increases in cycling lead to them being similar to the comparison group in their frequency of cycling. Results indicated that car-share was a substitute mode for cycling in this context.

In summary, the changes in cycling with new infrastructure can be enormous and are well-researched, showing increases in usage that vary considerably. However, they do not necessarily differentiate changes in cycling as a mode from changes in cycling route-choice.

4.8.1.2 Changes in Car-Use with Cycling Infrastructure

An important UK project for the modal shift impacts of cycling infrastructure is the *iConnect* project, which informs the following two studies. This was, briefly, a study of the impact of a large infrastructure building project called Connect2, which covered 84 sites across the UK.

- Song et al. consider impacts at three of these sites: Cardiff, Kenilworth and Southampton (Song, Preston, and Ogilvie 2017). Each was a joint walking-cycling route project. In Cardiff, a route from a suburb (Penarth) to the city-centre, including a footbridge; in Kenilworth, a cycling/foot bridge across a busy dual carriageway and several cycle-routes, including to Warwick University; in Southampton, a raised broadwalk connecting the city centre to residential areas. Data collection, and these infrastructure projects, occurred around 2010-12 and on an annual basis. Within 5km of each site, large numbers of people (7,500) were sampled randomly using the electoral register. The baseline survey had a 15% response rate, dropping to around 6.7% across all three questionnaires, so 2010-11 and 2010-12 comparisons were undertaken to compensate for this low response rate, and age and gender were weighted, to allow for self-selection effects, which were manifest in (e.g.) higher numbers of women and better-educated people than were found in the population. There was no significant total change in active travel or car distances in the sample, with the exception of a change found in driving between 2010 and 2012, with respondents driving (on average, per week) 11 miles less as a driver and 8 miles more as a passenger. During 2010-12, 23% of respondents made a shift to active travel from car-use, but a similar number (approx. 20%) also did the opposite. Taken as a whole, these indicate reciprocal shifts between active travel and car-use over these one- and two-year periods but no obvious aggregate changes that could be attributable to contextual changes, such as new infrastructure, as the total active travel mileage did not significantly increase.

  To assess the role of the new infrastructure in accounting for modal choice, Song et al. analysed (using multiple regression) to what extent exposure to the new infrastructure was associated with observed changes (shifts) in modal split between active-mode and car-mode use, while allowing for some other explanatory factors (e.g., socio-demographic differences, access to cars and bicycles). Three exposure variables were considered in separate models: reported use of the new infrastructure, distance from the 'core' of the new infrastructure (e.g., a new bridge), and distance from the periphery of the roads/paths connected to the core infrastructure. The logic of this analysis is that if anyone would be encouraged to take up cycling for daily travel following the provision of new infrastructure, it would be those who live closest to it. While use of the infrastructure was found to be associated with an increased probability of having shifted to active travel from car-use by distance, both distance-based exposure variables were not statistically significant. This tends to limit the causal inference that new infrastructure, as new infrastructure, is connected to modal shifts. However, the authors interpret this pattern as suggesting that while the intervention was necessary for the increase in active travel as a mode, distance to the intervention was not sufficient to bring about the change. A key theme in their discussion of results appears to be recreational usage, as opposed to utility usage; it discussed as a transition whereby recreational users graduate to using walking/cycling for utility travel but, in the meantime, recreational usage may tend to limit association between infrastructural exposure and travel behaviour in the short term. In short, the modal shifts are modest by comparison to those in studies cited above with respect to cycling infrastructure usage alone.

- Le Gouais et al. used data across 4 years (2009-13) and 77 sites (with pre- and post-test data available) to investigate changes in the use of the infrastructure to understand who makes use of them (for walking or cycling), which types receive the most use, and which encourage physical activity (Le Gouais et al. 2021). The median increase in use of the infrastructure was +51.8% and increases of at least +100% were found for 22 of 77 sites, however, as with previous studies, modal shift was not estimated (except for some small exploration of this necessary to support a public health analysis). Estimating differences in use between sites, they found that sites with lower baseline walking/cycling showed greater increases, more population-dense areas. High Benefit Cost Ratios (BCRs) and doubling of peak time users were associated with the presence of a public transport interchange within 0.5 miles of the routes, suggesting that walking/cycling infrastructure can enhance public transport use by providing easier access to stops; however, the effect on public transport was not directly measured.

So, iConnect seems to have identified modest evidence for modal shift but quite strong evidence for increased walking/cycling using the new infrastructure. Wardlaw, undertaking an in-depth documentary comparison between cycling in the UK and the Netherlands since the 1950s (Wardlaw 2014), concluded that communities in the UK where cycling is most common are those with not only infrastructure but also ”strong campaigning groups and local authority commitment to cycling.” Wardlaw went on to observe that:

> Surprisingly, building cycle infrastructure in isolation does not necessarily have much effect. In the UK, there are a number of “new towns” built from scratch with good quality cycling networks separate from the road system. These include Milton Keynes, Stevenage, and Livingston. The network of Stevenage is of particularly high standard. Yet today it is neglected, and cycle use is low at 3% share of commuter trips (European Cyclist's Federation 2013). Early Dutch programmes mirrored this experience. Construction of networks in The Hague, Tilburg and Delft between 1975 and 1987 attracted existing cyclists but did not increase cycle use much overall (Wellman, 1999, p.43–44). […] The recovery [in Dutch cycling starting in the 1970s] had support across Dutch society and enjoyed government investment enduring decades, integrated with land planning, restrictions on car use and legal protection for cyclists.”

Van Goeverden et al. report the results of ‘classic’ Dutch studies of this vintage that “were not shared with the international scientific audience” at the time (van Goeverden et al. 2015). With respect to car-usage effects, questionnaire follow-ups asked respondents in these studies what mode they would have used had they not walked/cycled. This indicated shifts from car-use to cycling of between 2% and 5% across seven studies, the median being 2%; four studies considered shifts from any motorised transport, for which 3% to 11% was found (median 9.5%). Importantly, the findings for motorised transport more closely reflect those found for changes in bicycle use (ranging from around 0% to 30%) from counts and surveys, creating an ambiguity between whether it was the case that these infrastructure showed modest reductions in car-use because they were ineffective in this respect or whether this was due to historically lower rates of car-ownership: perhaps many more people who would drive today would have used public transport in the 1970's and 1980's.

Concerning to what extent walking/cycling infrastructure actually affects car-use as opposed to attracting existing cyclists/pedestrians, the research on this point is somewhat limited and mixed; literature is summarised by Pritchard et al. whose study (using strong GPS data but for a relatively small sample and low response rate) found no evidence for mode-change with the construction of cycling infrastructure in Oslo in 2017 (Pritchard, Bucher, and Frøyen 2019).

One report from Delft provides some further evidence (Wilmink, A. and Hartman, J. B. 1987). In 1982, around 75% of the city had a cycling network in place. These consisted of dedicated cycle paths in urban and suburban areas. The intervention also included traffic control and regulation measures. The study reported concerns the outcome of an extension of the network to two districts of the city, with a third undeveloped district as a comparison area. With respect to the context, however, it is important to appreciate that the modal split was 40% towards cycling (26% walking, 26% car use, 6% public transport) and that this rose to 43%: so cycling was already the dominant mode, and the net effect of the cycling network was not extensive (presumably, being only two districts). In the test areas, there was a 15% increase in cycle volume (7% attributed to increased cycling rather than route change), but car volumes "remained stable", between 1982 and 1985. While limited attention was given to car travel in this research, they report before-after changes in car-use in both an intervention area and control area. Driven distance in the intervention area increased by 10%, and by 13% in the control area, suggesting a -3% difference. On this basis, they concluded that the cycling infrastructure had 'restrained' growth in driving. In terms of modal share, they estimate an approximate 3.3% shift from car-use to bicycling, of which 1.9 percentage points are due to car-passengers and 1.4 to car-drivers.

Finally, a recent meta-analysis of intervention studies that promote cycling (Doğru, Webb, and Norman 2021) found that studies that included changes to the physical environment (such as cycling infrastructure) were less effective in promoting cycling than studies that did not; they did not anticipate this, but do identify several reasons to treat this findings with caution, including the difficulties of assessing effects of infrastructure changes (often made at the area level and without good control groups) and the lack of allowance for intensity (changes in the physical environment are not necessarily cycling infrastructure, but could be signage or other changes).

In summary, changes in car-use with cycling infrastructure is an under-researched topic, but such evidence as there is indicates relatively modest reductions in car-use by comparison to research concerning changes in the use of infrastructure for physically active travel.

4.8.2 Model

Given the research gaps identified above, we model increase in cycling as an assumption rather than policy lever. The user can apply a percentage increase in cycling (not counting e-bikes) which is then assumed to reduce use of other modes via established diversion factors.

4.9 Diversion factors

We take diversion factors for all of the above models from Dunkerly et al., Table A2 and Table 22 (Dunkerley et al. 2018), averaging where appropriate.

```
Intervention on: Car driver or passenger
 Length under 10 miles:
  Bus 0.3
  Rail 0.175
  Bicycle 0.05
  Walk 0.1
 Length over 10 miles:
  Bus 0.09
  Rail 0.65
  Bicycle 0
  Walk 0
Intervention on: Rail
 Length under 10 miles:
  Car 0.375
  Bus 0.325
  Bicycle 0.05
  Walk 0.025
 Length over 10 miles:
  Car 0.48
  Bus 0.15
  Bicycle 0
  Walk 0
Intervention on: Bus
 Length under 10 miles:
  Car 0.275
  Rail 0.20
  Bicycle 0.06
  Walk 0.2
 Length over 10 miles:
  Car 0.275
  Rail 0.55
  Bicycle 0
  Walk 0
Intervention on: Bicycle (not including E-bike)
 Length under 10 miles:
  Car 0.19
  Bus 0.19
  Rail 0.13
  Walk 0.19
 Length over 10 miles:
  All modes 0
```

This source treats both car drivers and passengers as a single mode, and therefore does not include diversion factors to/from car passenger. We therefore assume

1. The given diversion factors are correct for conversion of car passenger-miles to other mode passenger-miles, i.e. they are applied to car passengers as well as drivers.
2. The given elasticities of demand apply to car vehicle miles, i.e. when an elasticity of demand predicts reduced car miles,
    a. Passenger miles will be reduced and transferred to other modes (bus/rail/bicycle/walk) as per diversion factors in the literature.
    b. The majority of the reduction in driver miles will be transferred to other modes as per diversion factors in the literature. Those driver miles that remain must become either
        i. car passenger miles (for which the literature provides no diversion factor), or

ii. no-travel (which is usually assumed).

As the overall aim of the model is to study car vehicle miles (which in the absence of significant self-driving technology, are equivalent to car driver miles), the question of whether car-driver miles not diverted to another mode have been diverted to car-passenger, or no-travel, is not of great importance to us. By default we therefore assume a diversion to no-travel, however given that we are also allowing the user to examine the impact of altering average occupancy (below), we provide a slider "*Unaccounted diversion from driver to passenger*" which allows a proportion of the no-travel diversion factor inferred from the literature to be transferred instead to car passenger miles, to examine the impact on occupancy.

4.10 Car occupancy

In the absence of reliable evidence on policies to increase car occupancy (see "High Occupancy Vehicle Lanes" below) we implement car occupancy change as a top-down assumption without specifying how occupancy changes are to be achieved. The occupancy slider allows specification of a minimum average car occupancy. Where any combination of trip length/purpose/urban-rural category is showing *average* car occupancy below the desired minimum, driver miles are reallocated to passenger miles to achieve the specified level.

4.11 E-bikes

4.11.1 Background

Fishman and Cherry provide a useful all-purpose review of the literature on e-bikes (Fishman and Cherry 2016). An 'e-bike' ranges between a conventional bicycle with an electric motor (bicycle-style e-bike) and a very small electric scooter (scooter-style e-bike). The former is more commonplace in the US, Europe and Australia whereas the latter is more commonplace in Asia, and this division is also reflected in research. The key benefit of e-bikes over regular cycling is that the motor reduces the work necessary to move the bike, and hence removes or reduces some key barriers to cycling (physical fitness, age, topography, perspiration) and increases the potential range of travel achievable by bike. At the same time, the use of electric power avoids vehicular pollution and (to the extent that electrical generation can be made sustainable) has the potential to reduce carbon emissions from motorised transport. The research Fishman and Cherry cite with respect to modal shift could be described as 'early but encouraging': in China, much e-bike use substitutes for other motorised transport - scooter-style e-bikes have circumvented motor vehicle regulations in China, being bicycles legally - and tends not to substitute for conventional cycling; European and US research tended to show similar results, though using intervention designs due to the relatively low market penetration. We note, briefly, that Cairns et al. summarise many previous studies and interventions in the literature review introducing their study (Cairns et al. 2017).

Has subsequent research supported these early results, and has any research considered Vehicle Miles Travelled?

- Fyhri and Fearnley report an experiment where motorists were selected at random from the list at the Norwegian Automobile Federation and those agreeing to participate were sent to a local e-bike shop and their hire of an e-bike was paid for over a trial period, whereas participants in the control group just completed measurements but did not receive a paid e-bike trial period (Fyhri and Fearnley 2015). Surveys were used to collected self-report data, including travel behaviour. In the trial group, compared to their baseline, cycling as a share of total distance travelled increased by around 20% (it was about 30% greater than the control group, and the share in the control group did not change over time). A key limitation of this study was a high drop-out rate and a relatively low response-rate, which raises the risk of self-selection bias (i.e., perhaps only those positively inclined towards e-bikes participated and completed the study). In a similar study in Sweden, again, a similar reduction of 21% in car-distance was found (Söderberg f.k.a. Andersson, Adell, and Winslott Hiselius 2021).

- Fyhri and Beate Sundfør report similar research to Fyhri's 2015 study, but followed a small sample who had purchased their own e-bike, taking measures before-and-after and comparing measures to measures taken from a control group who only wanted to buy an e-bike (Fyhri and Beate Sundfør 2020). This largely replicated the findings of their earlier e-bike trial study (i.e., an increase in cycle-distance share of around 20%). We note that it is useful to consider that those few who persist in (do not drop-out of) a trial of an e-bike may resemble those who purchase their own e-bike in their motivations.
- Kroesen analysed panel data from three years of a national transport survey in the Netherlands to consider the extent e-bikes substitute for car-travel (Kroesen 2017). E-bike owners were found to travel less distance on average by both car (-28%, -5.8km) and public transport (-64%, -9.4km). A statistical model (a structural equation model) was also created to explain mode-use distance as a function of both vehicle ownership variables and socio-demographic differences. Here, e-bike use was found to be associated with car-use and public transport use negatively, suggesting that e-bike use substitutes for these alternatives. Importantly, however, while e-bike ownership seemed to substitute for conventional bike ownership, e-bike ownership did not substitute for car ownership: there was a small positive correlation between the two. It is important to consider the context: the Netherlands has a strong cycling culture by comparison to the UK and there has been a fast uptake of e-bikes in the Netherlands (Fishman and Cherry 2016), both of which may be enabling factors for a substitution of e-bike use for car use.
- Söderberg et al. (Söderberg f.k.a. Andersson, Adell, and Winslott Hiselius 2021) summarised Sun et al. (Sun et al. 2020) who conducted similar research to Kroesen (Kroesen 2017) using the same data-source, but with the key difference of implementing a before-after (within subjects) design rather than comparing e-bike owners to non-owners (between subjects). Interestingly, but as one might expect, they show that the substitution from other modes applies to shorter-distance journeys; car-journeys of 15km or fewer are reduced, but those beyond this distance are unaffected. Cairns et al. report an e-bike trial study amongst employees (N=80) of two large employers in the city of Brighton, which was chosen as a location in the UK where people might be more amenable to e-bikes (Cairns et al. 2017). The study employed mixed qualitative and quantitative methods but, on the other hand, did not have a non-intervention control group. An annual follow-up indicated that the trial may also have been relatively successful as an intervention, encouraging participants to invest in their own e-bike.

Although this is only a brief review, these studies seem consistent in showing car-distance reductions of about 20% (10%-30%). However, in sampling those few who obtain their own e-bikes (early adopters) and those few who do not drop-out of trial studies, observed reductions may begin to diminish to the extent that other segments of the market may find e-bikes less useful for their transport needs. A recent review by Jenkins et al. takes note of several barriers to adoption – safety, weight, purchase-cost, battery-charging availability – in addition to traditional barriers to cycling – e.g., weather, lack of cargo/passenger capacity (Jenkins et al. 2022). So, a financial intervention (e.g., incentives offered through workplaces for commuting), they suggest, might help encourage adoption, as well as improvements in infrastructure and the environment to encourage cycling generally by making it safer and more pleasant. They also point to the importance of extending safety legislation concerning bicycles to cover e-bikes, too, and to incorporate e-bikes within driver awareness training (i.e., driving tests).

4.11.2 Trip length distribution for e-bikes

Evidence on trip length distributions for e-bikes was limited. Cairns et al., in reviewing available evidence, report that "e-bikes can encourage relatively long cycle trips", listing five studies that each found e-bike cycling distances to be greater than one might expect, namely 6.09 miles, 7.08 miles, 9.01 miles, 11.18 miles and 18.64 miles (Cairns et al. 2017). We were unable to obtain the text of three of these five studies. The 18 miles estimate is from a (to our knowledge) unpublished study of an e-bike community loan scheme undertaken in the Brecon Beacons in Wales (Kidd and Williams 2009). The study was undertaken with relatively few individuals (less than 50) but the numbers reported indicate (though it is not stated) that distance measurements were objectively measured. Engelmoer provided the 6.09 mile estimate in their Master's Thesis (Engelmoer 2012) citing a report from the Netherlands (Hendriksen, Engbers, and Schrijver 2008) which we could not obtain. Engelmoer reports that this was a survey study of 1,448 people in 2007, of whom 1.9% owned e-bikes (hence around 28 respondents).

Bourne et al. reviewed literature to better understand different impacts of e-bikes upon cycling, considering distances too, however the focus on health (where distance over days/weeks is more important than distance at the trip level) leads to the literature summarised being less relevant (Bourne et al. 2020). Hasnine et al. simulate policy impacts on e-bike distances using a model estimated from travel survey data in Toronto, however it is not clear whether these distances are per-trip or weekly (Hasnine, Dianat, and Habib 2020).

4.11.3 Model

Given the limited evidence on how to encourage modal shift to e-bikes, we include this as a top-down assumption, allowing the user to set the percentage of people who use an e-bike. Following the literature above, these people are then assumed to travel 20% fewer car miles overall, albeit with the reduction in distance coming from trips under 25 miles in length. It is important to note that, based on the literature above, this reduction in car miles is unlikely to be directly caused by the purchase of an e-bike. Rather, the purchase of an e-bike likely reflects an underlying lifestyle choice which is also responsible for the reduction in car miles. For this reason we label this model control as 'e-bike lifestyle' to emphasize the importance of underlying motivations and reflect that, for example, distributing free e-bikes to car users in isolation is unlikely to achieve this level of car mile reduction.

From Hendriksen et al. 2008 (in Fig. 13 of Engelmoer) we sum area under the curve to estimate that the total distance covered by e-bike trips in the 10-25 mile band is approximately 30% of the total distance covered by e-bike trips under 10 miles (Hendriksen, Engbers, and Schrijver 2008; Engelmoer 2012). Note that we do not take the absolute mode shares in this figure to be relevant to the UK currently, as they are derived from the Netherlands; we are in this case only interested in deriving a ratio of short to long e-bike trips for our own use.

Returning to the TrafRed model, we find that applying a 47% total mileage reduction from car trips under 10 miles, and a 16% mileage reduction in the 10-25 mile band (in which we assume the majority of the reduction is in the lower part of this band, i.e. the 10-15 mile range) gives a 20% car mile reduction overall, while preserving the 30% ratio of short to long e-bike trips derived above. This is applied to the relevant proportion of both car and public transport miles as specified using the e-bike uptake sliders.

4.12 Teleworking

4.12.1 Background

A review of the teleworking and transport evidence is provided by the Victoria Transport Policy Institute in their online encyclopaedia of transport demand management (Victoria Transport Policy Institute 2019). This identifies some key considerations in seeking evidence concerning the policy aspects.

- Not all work is intrinsically suitable for teleworking. This limits potential transport effects.
- Telecoms infrastructure and facilities (e.g., internet) are necessary for home-working.
- Offering similar financial support to both commuters and non-commuters to cover their costs.
- Not everyone works well at home; not all homes make suitable workplaces.
- Teleworking is attractive to long-distance commuters, making it effective in reducing travel.
- There are rebound effects (4 or 5 listed), which limit (or reverse) car-use reductions, potentially.

The review concludes: "telecommunications can have complex and difficult to predict impacts on overall vehicle travel. For Telework to provide significant vehicle travel reductions it must be implemented in conjunction with other TDM strategies that provide an incentive to reduce driving".

Thomas et al. wrote a report for the New Zealand government concerning teleworking policies that is useful in summarising policy-effectiveness in encouraging home-working (Thomas et al. 2021). A recent systematic review has been made on the effect of teleworking on energy use (Hook et al. 2020), and this also presents evidence from studies of teleworking and VMT. They identified 26 studies that reported this as the outcome metric, ranging from a 3.9% increase to a 20% reduction and with the majority of studies reporting reductions. However, they are critical of the limited scope of these studies (to those involved, to commuting alone, to car-use alone) and a theme of the review is that a few studies with greater scope have tended to be more likely to report inconclusive effects or increases, rather than decreases, when factors such as changes in commute-distance and differences in non-work travel are also considered. Hook et al., hence, acknowledge the potential indicated by the majority of evidence while being doubtful of overall results. Elldér, published after Hook et al. (2020), reports survey-based evidence in support of teleworking reducing vehicle miles travelled in Sweden, in 2011-16 (Elldér 2020). The author notes that this result could be due to the Scandinavian context (most studies are from the USA) and to the data used being up-to-date and so more likely to have captured home-working as a modern societal norm and one increasing supported by IT developments. This study also reported that VMT tends to only reduce substantially for full-day teleworkers, but actually increases for part-day teleworkers (each by comparison to non-teleworkers).

So, the exact form of the intervention is of potential importance. A compulsory requirement for employers to offer home working days would enable increased home-working, but it would not necessarily ensure that additional car-distance does not take place on those days, or that other decisions do not result in increased car-distance on days where commuting does take place. Another approach might be to include this as a policy, but add an additional measure to reduce car-use (as VTPI indicated) into the description.

4.12.2 What proportion of jobs can support teleworking?

As mentioned above, not all work is intrinsically suitable for teleworking. This limits potential transport effects. Therefore, it is useful to know what proportion of jobs can support teleworking in order to understand the potential transport effects. Matthews and Williams estimate that 40% of jobs in the USA and 45% in Japan can support teleworking, based on sectoral employment statistics and reasonable assumptions (Matthews and Williams 2005). Dingel and Neiman estimate this to be 37% in the USA, these account for 46% of US wages (Dingel and Neiman 2020). Their approach was similar to that of Matthews and Williams (i.e., making reasonable inferences), but applied to national occupational survey data, which was used to classify ISCO job classifications as being capable of home working. This allowed the results to be used to investigate this percentage across a range of countries. Great Britain is estimated to have a percentage of 43-44%. A working paper by Hatayama et al., using a similar methodology, puts this figure at about 31% in the UK (Hatayama, Viollaz, and Winkler 2020). A survey by The Decision Maker Panel at the Bank of England, made during the recent COVID-19 global pandemic, estimated that 37% of jobs in the UK were done from home in 2020 (Office for National Statistics 2021). On this basis, 30% to 40% seems to be a reasonable estimate for the proportion of jobs in the UK that can support teleworking.

4.12.3 What proportion of employees in those jobs will take up teleworking if the employer is compelled to offer it?

The question of how many employees will telework voluntarily if given the opportunity is also relevant to the extent of potential teleworking transport effects. Therefore, studies of changes in workplace policy would be relevant. Summarising previous relevant studies, Stefaniec et al. cite survey research from Europe during the pandemic where preference for continued homeworking was gauged (Stefaniec et al. 2022). In a Netherlands sample of workers, 68% showed interest in adding at least one additional day of teleworking to their pre-covid work-patterns after the lifting of restrictions, and 63% of Flemish employees expressed a similar willingness. The ONS surveyed UK home-working workers during the pandemic and found that 85% wanted to use a "hybrid" approach of both home and office working in future (Office for National Statistics 2021). Stefaniec et al., surveying workers in Ireland in 2021, found 78% were positive towards homeworking post-covid; however, only 13-16% indicated that they would wish to work from home full-time (Stefaniec et al. 2022). On this basis, 70% would seem to be a relatively cautious estimate for adoption of working from home to some extent.

4.12.4 Model

Given the lack of evidence on how to encourage employers to allow teleworking, we implement this as a top down assumption. The user may set a maximum of 40% employers allowing teleworking (based on the maximum proportion of jobs suitable for teleworking identified above). People within these jobs are then assumed to reduce their commute mileage by 70%. We emphasize that this does not include rebound effects, e.g. people choosing to live further from the office in the event that the employer is open to teleworking, and hence commuting further on days when they do make the journey.

4.13 Costs and revenue

The cost model is basic, and intended only to give a rough idea of whether road use charges are able to raise funds to a similar level as the user chooses to spend on public transport subsidy.

All costs are inflation adjusted to 2019.

Any cost paid by motorists due to road use charging, parking and congestion charges is applied as revenue.

The cost model covers state expenditure on public transport (we do not distinguish between local authorities and national government). Expenditure is based on current government subsidy paid per passenger mile, plus any proportion of fares subsidised. Both subsidy and fares are assumed to remain constant on a per-mile basis, prior to application of any fare subsidy.

Neither fare income nor operating costs are directly included, as we assume these are accrued to/borne by the private or franchise service provider.

The state cost of bus and rail is therefore deemed to be:

(current subsidy per mile + proportion of fare subsidized x average fare per mile) x total passenger miles

Average fare and subsidy data is as follows:

- Bus fares from BUS0402. Great Britain 2019 (2019 prices) 143p/journey
- Rail fares from Rail table 1210. Revenue per franchised pkm, 15.47p (2019, 2019 prices)
- Bus subsidy per journey 2015 5.4p
- Rail subsidy 2015 5.6p/mile
- Correction for GDP inflation 2015-2019 from TAG Data Book annual parameters: 116.89/108.27

We display only cost changes from the current baseline, i.e. we subtract *current subsidy per mile x baseline passenger miles* from the figures shown in the model outputs.

By default, costs are assumed to scale per passenger mile. This provides an estimate of cost based on ridership, but is not appropriate in the case of increasing service frequency, as more frequent services divide passenger numbers over a greater number of vehicles, and should therefore be expected to cost more per passenger mile.

A second cost computing mode is therefore provided, "Divide per-passenger-mile costs by occupancy", where occupancy is modelled as a percentage change from baseline, increasing with ridership but decreasing with service frequency (capacity of vehicles is not modelled). This is intended as a more appropriate choice for modelling increases in service frequency, but will underestimate costs arising from increased ridership. This mode may be appropriate in cases where existing services are relatively unoccupied so greater passenger numbers can be carried at negligible marginal cost.

Neither cost mode takes into account the cost of exceeding the maximum capacity of existing vehicles and infrastructure, a point at which – in practice – a sharp increase in cost per mile will occur. For local authorities where rail services are near to capacity, the TrafRed cost model is unlikely to be appropriate.

5 Effects not modelled

The following effects were considered for inclusion, but rejected for the reasons given below.

5.1 Expansion of rural bus network

Expansion of the bus network to rural locations currently unserved is not possible to model with an elasticity framework (as elasticity cannot account for an increase from zero).

The CPRE "Every Village Every Hour" report (Hinchliff and Taylor 2021) is a feasibility study for expansion of the rural bus network. It assumes uplift of 80% to 220% on existing commercially viable "arterial" bus routes, but does not assume significant ridership on new "capillary" routes. We note that TrafRed predicts bus uplift of 60% if frequency is increased by a factor of 4. However this equates to only 1% reduction in car miles overall.

Overall, increase of rural bus network (though desirable for social reasons) will have only minor impact on national mode share due to the smaller rural population, and risks a net increase in carbon emissions if services are underutilized.

Although rural areas currently have the highest car mode shares, urban areas have larger potential for reduction of car use due to their greater population.

Car mile reduction (as percentage of national total) if bus mode share…	…increases to 9% (equivalent to London bus)	…increases to 21% (equivalent to London bus + underground)
Conurbation	3%	8%
City/Town	5%	12%
Rural Town	1%	3%
Rural Village	2%	4%

5.2 High Occupancy Vehicle Lanes (HOVs)

A useful and up-to-date introduction to current research was available in one research article (Cohen et al. 2022). Cohen et al. indicate a lack of existing evidence concerning the effectiveness of HOVs in either traffic reduction or car-sharing. (a) Much of the evidence is stated preference survey evidence or modelling, rather than 'hard' empirical evidence about outcomes; (b) much as the empirical evidence for car-pooling is limited, so is the evidence concerning car-sharing resulting from HOVs (sensor data does not often record occupancy). This is consistent with the previous evaluation made by Santos et al., that this policy is frequently implemented (e.g., in the USA) but is not well understood (Santos, Behrendt, and Teytelboym 2010).

The larger correlational evidence that HOVs are associated with car-sharing in the USA appears convincing, however. Javid et al present a simple model (from stated carpooling in national survey data) showing clear positive relationships between the road-length of HOVs in US states and the extent of carpooling in those states, whilst allowing for a small number of key predictors, e.g., travel time and gasoline prices (Javid, Nejat, and Hayhoe 2017). In simple linear regression, length of HOV explains about 20% of the variance (B = 0.447). However, this is substantially greater when assessed at the smaller-unit county-level (N=58) within the state of California (the only state with sufficient HOVs to allow such a comparison): here, about 48% of the variance is explained by HOV length (B = 0.695), indicating that the effect can apply at a more specific level, where some factors (e.g., fuel prices, state-level policy) are more comparable. The main purpose of this research was to estimate emissions impacts and, in these, the greatest emissions reductions were estimated for more population-dense areas. It is important to consider the this is correlational 'macro' scale evidence, with the limitations this involves, and that the US context may not generalise well to the UK.

Cohen et al. point out that one of the main barriers to car-sharing is logistical (large 'costs' to finding riders), and digital lift-sharing may be synergistic with HOVs in encouraging car-sharing. In their study, they used data collected from a car-sharing platform both before and after the introduction of three HOVs in Israel in 2019 (Cohen et al. 2022). Importantly, two of these three HOVs were (essentially) the same North-South highway in different directions, whereas the third was a single South-North lane connecting a Southern city to the centre of the country, but not back again. The platform was a matching service, and they found that the 'intervention' increased both those seeking a rider and those offering to be a rider, but that this was only for the two North-South HOVs, indicating that bi-directional travel could be important; the South-North route was also a 3+ lane (the other a 2+ lane), which may have compounded the issue – finding two passengers rather than one passenger may limit the feasibility of HOV lane journeys. Spillover effects were also found: lift-shares not including the HOVs increased, suggesting encouragement of more general modal shifts as people began to use the platform and share trips. It is important to note that this 'natural experiment' appears to coincide with an increasing general popularity of ride-sharing platform usage, so this may be a necessary condition for HOV success. Three periods, a 1-month baseline, a 1-month immediate follow-up, and a 1.5-month later follow-up were compared for HOV and non-HOV routes, and a 76.5% greater increase was shown in immediate follow-up for HOV trips and a 60.1% greater increase in the later follow-up. Periods did, also, differ in degree of rules enforcement, with the immediate period being a period of 'soft' enforcement. Another factor is the degree of success of time savings, which the study estimated as being between 20% and 50%, so such car-sharing might not transpire if a HOV does not achieve travel-time reduction. The use of a single platform is also a limitation of the study, and it is hard to say how much of the increase is due to existing car-sharers migrating to the platform and to HOVs. Finally, this study was undertaken over a relatively short period of time, and it would be instructive to supplement this with long-run evidence.

A second study of potential use on empirical background is from Jakarta (Hanna, Kreindler, and Olken 2017). The policy in this context was that 3+ occupation was compulsory during rush-hour in the city Central Business District and on the main arterial motorway; this was the case from 1992 to 2016, with the policy being unchanged since 2004. This policy was abandoned, and Hanna et al. studied (using mobile phone data) what happened afterwards, finding that there were substantial increases in travel time following the policy change, and irrespective of whether the routes were within the zones in question. Contextual factors are important to consider, though, because this is different from a UK context in important respects. (1) Jakarta is extremely large and extremely car-dependent at this time. (2) The policy in question was perhaps one of the most extreme examples of a HOV policy implemented. (3) The policy was failing (due to perverse incentives)[2] to create genuine shifts from driving to lift-

[2] Normal in the USA is 'slugging' - hitchhiking to make up the numbers on HOVs and similar schemes, and also in response to rising fuel prices (Boysen et al. 2021). In Jakarta, this had become a job: drivers were paying 'car jockeys' to ride in the car to make up the numbers, and these people would presumably spend all day riding back and forth in different cars. Wiseman (2019) describes this as a 'cobra problem' - when you pay a bounty on cobras,

sharing and it is possible that the effects were due to the great deal of help that even a little bit of extra passenger-travel made in the knock-on network effects of very extreme amounts of congestion ('hyper congestion').

(a) To summarise, the effect of HOVs appears to be mediated by car-sharing (shifts from driver to passenger journeys) and, hence, barriers and facilitators of car-sharing are likely to be influential (e.g., ride sharing platforms). HOVs, when effective, can have complementary knock-on effects upon non-HOV surrounding roads. HOVs have had mixed practical success (Wiseman 2019): in such cases as they have been unpopular or under-used, they can get converted into toll-lanes, HOTs, or normal road lanes. Although evidence is scarce, there is the suggestion that HOVs can increase car-use by encouraging shifts from public transport to car-passenger riding, which is a concern. Specifically, Johnson and Ceerla, when HOVs were relatively new, modelled a 4% increase in VMT with a HOV scenario (compared to a 'do nothing' scenario) in Sacramento, California (Johnston and Ceerla 1996).
(b) Shewmake (2012a) wrote an interesting SSRN pre-print or working paper on this subject specifically (Shewmake 2012a) prior to publishing an article in the same year (Shewmake 2012b). Despite describing quite difficult analytic work, working-paper results were ambiguous: without a statistical correction for area-level data in a multilevel framework, the analysis predicted citywide increases in VMT of 2% to 3%, whereas with this correction, citywide decreases in VMT of 2% were predicted; other analytic approaches yielded similarly ambiguous or non-significant results.

HOV can also increase car-sharing (Javid, Nejat, and Hayhoe 2017; Cohen et al. 2022) while having an ambiguous (or no) effect on VMT (Shewmake 2012a; 2012b) through the phenomenon of induced demand: building road-infrastructure encourages car use, which cancels-out the savings in VMT due to increased car-sharing. Volker and Handy provide a useful report to the US National Center for Sustainable Transportation on this subject, which includes an elasticity estimate of between +0.67 and +1.0 for lane mile length to VMT (Volker and Handy, Susan L. 2022). To the extent that induced demand explains these outcomes, the re-zoning of 'failed' HOVs as normal road lanes (or toll-lanes or HOTs) is concerning, as this would potentially 'lock in' any increase in car-use due to induced demand, in the absence of the practical means or the political will to remove the new infrastructure altogether.

5.3 Incentivising lift sharing

'Lift sharing' (aka car sharing, ride sharing, carpooling) is being a car-passenger in someone else's car; the innovation is the digital service, permitting this form of mobility as a service. Examples include Liftshare (Liftshare 2023) and Gocarshare (Gocarshare 2023) for general use, however many workplaces offer a similar service for workers. According to De Jong and Gun, the Netherlands National Model System (NMS) and the Norwegian national model use elasticities of 0.15 and 0.14, respectively, for the "long-term fuel price elasticity of the number of kilometres as car passenger" (de Jong and Gunn 2001).

someone starts a cobra farm; when the bounty is revoked, the cobras are released, and there are more cobras than before (in this case, people only use HOV lanes when roads are congested, so if you remove the problem then people do not use the lanes) (Wiseman 2019).

We do not separately model this as the key literature on increasing lift share relates to increasing cost of car use, which we already model elsewhere.

6 Limitations

We briefly note the following model limitations.

1. TrafRed is an economic model, not a transport network model. Modal splits are based on national averages of mode share for each trip length, and trip lengths are based in turn on national averages for each urban/rural category. So for example, in local authorities with limited rail network, the TrafRed model will overestimate the potential for railway use, as it is based on a national average and is agnostic of any deficiency in local rail network availability.
2. Trip length is not affected by trip purpose, and modal split is not affected by rural category (except indirectly via trip length). Incorporating these relationships would be a potential future upgrade to the model.
3. We do not model the impact of congestion on bus operator costs, as we don't have a flow model for the congestion levels. In reality a positive feedback loop is likely to exist whereby bus operator costs reduce as road traffic reduces (fewer services are required to maintain a given frequency).
4. We do not model varied impact of public transport fares depending on car occupancy, i.e. a family switching to bus must buy multiple tickets (the elasticity and diversion factor evidence base does not have the detail required to model this).
5. The baseline is derived from the National Travel Survey which does not cover Wales; we therefore have to assume the urban/rural travel profiles sampled in England are also applicable in Wales.
6. We do not model capacity of existing services and particularly rail infrastructure, and therefore the model will underestimate costs where modelled ridership exceeds maximum capacity (see 4.13).
7. Rail diversion factors will change if the rail system is at capacity – likely in reality more of the extra rail traffic would have to use bus. This highlights the need for a spatial model linking to rail capacity.
8. We don't model the possible difference between small-scale and larger-scale application of some of the policy levers - or the short-term and long-term impacts of applying them. We use long-run elasticities of demand, which are typically based on small changes over a medium term (3-6 year) time frame but not likely to capture long term land-use/transport feedback effects.
9. Large price changes modelled via elasticity will be of limited accuracy. Further research is needed to determine the size of price change from which this limitation is of concern.
10. We don't model interactions (combined impact) between the various policy interventions, as could be captured by a discrete choice model for mode choice
11. The modelling of improved walking or cycling networks is limited, and again does not consider interactions with other modes, in particular the use of active travel to access the public transport network.
12. For congestion charges, we model the response to average trip cost, but do not model the potential for people to group all their trips into a single day rather than reduce their car mileage. Mileage reduction from congestion charges is therefore likely to be marginally less than shown.

13. The model scope was limited to car mileage reduction, however the underlying aim is to reduce carbon emissions, which would be better modelled explicitly.
14. In any case, reducing carbon emissions isn't the only goal of local or national transport policy. The optimal policy package might involve greater investment in reducing public transport fares (e.g. to achieve social inclusion objectives) and/or active travel networks (e.g. to achieve health and other objectives), than one that was focused solely on achieving carbon-reduction objectives.

References

Abrate, Graziano, Massimiliano Piacenza, and Davide Vannoni. 2009. "The Impact of Integrated Tariff Systems on Public Transport Demand: Evidence from Italy." *Regional Science and Urban Economics* 39 (2): 120–27. https://doi.org/10.1016/j.regsciurbeco.2008.05.014.

Alhassan, Ilyas B., B. Matthews, Jeremy P. Toner, and Yusak O. Susilo. 2020. "The Movingo Integrated Ticket: Seamless Connections across the Mälardalen Region of Sweden." *Transportation Planning and Technology* 43 (4): 404–23. https://doi.org/10.1080/03081060.2020.1747204.

Amatuni, Levon, Juudit Ottelin, Bernhard Steubing, and José M. Mogollón. 2020. "Does Car Sharing Reduce Greenhouse Gas Emissions? Assessing the Modal Shift and Lifetime Shift Rebound Effects from a Life Cycle Perspective." *Journal of Cleaner Production* 266 (September): 121869. https://doi.org/10.1016/j.jclepro.2020.121869.

Audouin, Maxime, and Matthias Finger. 2019. "Institutions, Organizations, and Technological Innovations: The Dynamic Development of Smart Ticketing Schemes in London's Urban Transportation System." In *The Governance of Smart Transportation Systems*, edited by Matthias Finger and Maxime Audouin, 189–206. The Urban Book Series. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-96526-0_10.

Blythe, Philip. 2004. "Improving Public Transport Ticketing through Smart Cards." *Proceedings of the Institution of Civil Engineers - Municipal Engineer* 157 (1): 47–54. https://doi.org/10.1680/muen.2004.157.1.47.

Bourne, Jessica E., Ashley R. Cooper, Paul Kelly, Fiona J. Kinnear, Clare England, Sam Leary, and Angie Page. 2020. "The Impact of E-Cycling on Travel Behaviour: A Scoping Review." *Journal of Transport & Health* 19 (December): 100910. https://doi.org/10.1016/j.jth.2020.100910.

Boysen, Nils, Dirk Briskorn, Stefan Schwerdfeger, and Konrad Stephan. 2021. "Optimizing Carpool Formation along High-Occupancy Vehicle Lanes." *European Journal of Operational Research* 293 (3): 1097–1112. https://doi.org/10.1016/j.ejor.2020.12.053.

Cairns, S., F. Behrendt, D. Raffo, C. Beaumont, and C. Kiefer. 2017. "Electrically-Assisted Bikes: Potential Impacts on Travel Behaviour." *Transportation Research Part A: Policy and Practice* 103 (September): 327–42. https://doi.org/10.1016/j.tra.2017.03.007.

Campaign for Better Transport. 2018. "Integrated Transport: A New Generation of Interchanges." https://bettertransport.org.uk/wp-content/uploads/legacy-files/research-files/integrated-transport-a-new-generation.pdf.

Campos Ferreira, Marta, Teresa Galvão Dias, and João Falcão e Cunha. 2020. "An In-Depth Study of Mobile Ticketing Services in Urban Passenger Transport: State of the Art and Future Perspectives." In *Advances in Computational Intelligence and Robotics*, edited by João M.F. Rodrigues, Pedro J.S. Cardoso, Jânio Monteiro, and Célia M.Q. Ramos, 145–65. IGI Global. https://doi.org/10.4018/978-1-7998-2112-0.ch008.

Cohen, Maxime C., Alexandre Jacquillat, Avia Ratzon, and Roy Sasson. 2022. "The Impact of High-Occupancy Vehicle Lanes on Carpooling." *Transportation Research Part A: Policy and Practice* 165 (November): 186–206. https://doi.org/10.1016/j.tra.2022.08.021.

CoMoUK. 2019. "England & Wales Car Club Annual Survey 2017/18."

———. 2022a. "Car Club Annual Report United Kingdom 2021." https://uploads-ssl.webflow.com/6102564995f71c83fba14d54/62a8acc694bf3158d04ebd5d_CoMoUK%20UK%20Car%20Club%20Report%202021%20Key%20Findings.pdf.

———. 2022b. "Shared Cars: Overview and Benefits." https://www.como.org.uk/shared-cars/overview-and-benefits.

Croci, Edoardo. 2016. "Urban Road Pricing: A Comparative Study on the Experiences of London, Stockholm and Milan." *Transportation Research Procedia* 14: 253–62. https://doi.org/10.1016/j.trpro.2016.05.062.

Department for Transport. 2010. "DfT Announces Reform of Public Bodies." https://www.gov.uk/government/news/dft-announces-reform-of-public-bodies.

———. 2014. "Connectivity Travel Time Indicators for Major Road Junctions (CON03)." June 11, 2014. https://www.gov.uk/government/statistical-data-sets/connectivity-travel-time-indicators-for-major-road-junctions-con03.

———. 2022a. "Car Clubs: Local Authority Toolkit." https://www.gov.uk/government/publications/car-clubs-local-authority-toolkit/car-clubs-local-authority-toolkit.

———. 2022b. "Travel Time Measures for the Strategic Road Network and Local 'A' Roads: July 2021 to June 2022." September 8, 2022. https://www.gov.uk/government/statistics/travel-time-measures-for-the-strategic-road-network-and-local-a-roads-july-2021-to-june-2022.

Department for Transport and Active Travel England. 2020. "Gear Change: A Bold Vision for Cycling and Walking." https://www.gov.uk/government/publications/cycling-and-walking-plan-for-england.

Dingel, Jonathan I., and Brent Neiman. 2020. "How Many Jobs Can Be Done at Home?" *Journal of Public Economics* 189 (September): 104235. https://doi.org/10.1016/j.jpubeco.2020.104235.

Doğru, Onur Cem, Thomas L. Webb, and Paul Norman. 2021. "What Is the Best Way to Promote Cycling? A Systematic Review and Meta-Analysis." *Transportation Research Part F: Traffic Psychology and Behaviour* 81 (August): 144–57. https://doi.org/10.1016/j.trf.2021.06.002.

Dunkerley, Fay, Mark Wardman, Charlene Rohr, and Nils Fearnley. 2018. *Bus Fare and Journey Time Elasticities and Diversion Factors for All Modes: A Rapid Evidence Assessment*. RAND Corporation. https://doi.org/10.7249/RR2367.

Elldér, Erik. 2020. "Telework and Daily Travel: New Evidence from Sweden." *Journal of Transport Geography* 86 (June): 102777. https://doi.org/10.1016/j.jtrangeo.2020.102777.

Engelmoer, Wiebe. 2012. "The E-Bike: Opportunities for Commuter Traffic." University of Groningen. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=f5f169f6f439b03731cb74630b26049b4a3dccc9.

Félix, Rosa, Paulo Cambra, and Filipe Moura. 2020. "Build It and Give 'em Bikes, and They Will Come: The Effects of Cycling Infrastructure and Bike-Sharing System in Lisbon." *Case Studies on Transport Policy* 8 (2): 672–82. https://doi.org/10.1016/j.cstp.2020.03.002.

Fishman, Elliot, and Christopher Cherry. 2016. "E-Bikes in the Mainstream: Reviewing a Decade of Research." *Transport Reviews* 36 (1): 72–91. https://doi.org/10.1080/01441647.2015.1069907.

FitzRoy, Felix, and Ian Smith. 1998. "Public Transport Demand in Freiburg: Why Did Patronage Double in a Decade?" *Transport Policy* 5 (3): 163–73. https://doi.org/10.1016/S0967-070X(98)00024-9.

———. 1999. "Season Tickets and the Demand for Public Transport." *Kyklos* 52: 219–38. https://doi.org/10.1111/j.1467-6435.1999.tb01443.x.

Frank, Lawrence D., Andy Hong, and Victor Douglas Ngo. 2021. "Build It and They Will Cycle: Causal Evidence from the Downtown Vancouver Comox Greenway." *Transport Policy* 105 (May): 1–11. https://doi.org/10.1016/j.tranpol.2021.02.003.

Fyhri, Aslak, and Hanne Beate Sundfør. 2020. "Do People Who Buy E-Bikes Cycle More?" *Transportation Research Part D: Transport and Environment* 86 (September): 102422. https://doi.org/10.1016/j.trd.2020.102422.

Fyhri, Aslak, and Nils Fearnley. 2015. "Effects of E-Bikes on Bicycle Use and Mode Share." *Transportation Research Part D: Transport and Environment* 36 (May): 45–52. https://doi.org/10.1016/j.trd.2015.02.005.

Geels, Frank W. 2019. “Socio-Technical Transitions to Sustainability: A Review of Criticisms and Elaborations of the Multi-Level Perspective.” *Current Opinion in Environmental Sustainability* 39 (August): 187–201. https://doi.org/10.1016/j.cosust.2019.06.009.

Gibson, Matthew, and Maria Carnovale. 2015. “The Effects of Road Pricing on Driver Behavior and Air Pollution.” *Journal of Urban Economics* 89 (September): 62–73. https://doi.org/10.1016/j.jue.2015.06.005.

Gilbert, Christopher L., and Hossein Jalilian. 1991. “The Demand for Travel and for Travelcards on London Regional Transport.” *Journal of Transport Economics and Policy* 25 (1): 3–29.

Gocarshare. 2023. “GoCarShare - Car Sharing Made Fun.” https://gocarshare.com/.

Goeverden, Kees van, Thomas Sick Nielsen, Henrik Harder, and Rob van Nes. 2015. “Interventions in Bicycle Infrastructure, Lessons from Dutch and Danish Cases.” *Transportation Research Procedia* 10: 403–12. https://doi.org/10.1016/j.trpro.2015.09.090.

Government Digital Service. 2023. “Driving Lessons and Learning to Drive.” 2023. https://www.gov.uk/driving-lessons-learning-to-drive.

Hanna, Rema, Gabriel Kreindler, and Benjamin A. Olken. 2017. “Citywide Effects of High-Occupancy Vehicle Restrictions: Evidence from ‘Three-in-One’ in Jakarta.” *Science* 357 (6346): 89–93. https://doi.org/10.1126/science.aan2747.

Hasnine, Md Sami, Alireza Dianat, and Khandker Nurul Habib. 2020. “Investigating the Factors Affecting the Distance Travel and Health Conditions of E-Bike Users in Toronto.” *Transportation Research Interdisciplinary Perspectives* 8 (November): 100265. https://doi.org/10.1016/j.trip.2020.100265.

Hatayama, Maho, Mariana Viollaz, and Hernan Winkler. 2020. *Jobs’ Amenability to Working from Home: Evidence from Skills Surveys for 53 Countries*. World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-9241.

Hendriksen, I, L Engbers, and J Schrijver. 2008. “Elektrisch Fietsen, Marktonderzoek En Verkenning Toekomstmogelijkheden.” TNO/ BOVAG.

Hilferink, P., A. Roest Crollius, and J. C. Van Elburg. 2003. “Integration and Regulatory Structures in Public Transport: Costs and Benefits of Public Transport Integration.” NEA Transportonderzoek En-Opleiding.

Hinchliff, Christopher, and Ian Taylor. 2021. “Every Village, Every Hour: A Comprehensive Bus Network for Rural England.” Campaign to Protect Rural England.

Hong, Jinhyun, David Philip McArthur, and Mark Livingston. 2020. “The Evaluation of Large Cycling Infrastructure Investments in Glasgow Using Crowdsourced Cycle Data.” *Transportation* 47 (6): 2859–72. https://doi.org/10.1007/s11116-019-09988-4.

Hong, Jinhyun, David Philip McArthur, and Joanna L. Stewart. 2020. “Can Providing Safe Cycling Infrastructure Encourage People to Cycle More When It Rains? The Use of Crowdsourced Cycling Data (Strava).” *Transportation Research Part A: Policy and Practice* 133 (March): 109–21. https://doi.org/10.1016/j.tra.2020.01.008.

Hook, Andrew, Victor Court, Benjamin K Sovacool, and Steve Sorrell. 2020. “A Systematic Review of the Energy and Climate Impacts of Teleworking.” *Environmental Research Letters* 15 (9): 093003. https://doi.org/10.1088/1748-9326/ab8a84.

ITSO. 2023. “Facts & Figures : ITSO.” https://www.itso.org.uk/about-us/facts-figures/.

Janson, Michael, and David Levinson. 2014. “HOT or Not.” *Research in Transportation Economics* 44 (June): 21–32. https://doi.org/10.1016/j.retrec.2014.04.008.

Javid, Roxana J., Ali Nejat, and Katharine Hayhoe. 2017. “Quantifying the Environmental Impacts of Increasing High Occupancy Vehicle Lanes in the United States.” *Transportation Research Part D: Transport and Environment* 56 (October): 155–74. https://doi.org/10.1016/j.trd.2017.07.031.

Jenkins, Michael, Lucio Lustosa, Victoria Chia, Sarah Wildish, Maria Tan, Daniel Hoornweg, Meghann Lloyd, and Shilpa Dogra. 2022. “What Do We Know about Pedal Assist E-Bikes? A Scoping Review to Inform Future Directions.” *Transport Policy* 128 (November): 25–37. https://doi.org/10.1016/j.tranpol.2022.09.005.

Johnston, Robert A., and Raju Ceerla. 1996. “The Effects of New High-Occupancy Vehicle Lanes on Travel and Emissions.” *Transportation Research Part A: Policy and Practice* 30 (1): 35–50. https://doi.org/10.1016/0965-8564(95)00009-7.

Jong, Gerard de, and Hugh Gunn. 2001. “Recent Evidence on Car Cost and Time Elasticities of Travel Demand in Europe.” *Journal of Transport Economics and Policy* 35 (2): 137–60.

Kamargianni, Maria, Weibo Li, Melinda Matyas, and Andreas Schäfer. 2016. “A Critical Review of New Mobility Services for Urban Transport.” *Transportation Research Procedia* 14: 3294–3303. https://doi.org/10.1016/j.trpro.2016.05.277.

Karpinski, Elizabeth. 2021. “Estimating the Effect of Protected Bike Lanes on Bike-Share Ridership in Boston: A Case Study on Commonwealth Avenue.” *Case Studies on Transport Policy* 9 (3): 1313–23. https://doi.org/10.1016/j.cstp.2021.06.015.

Kent, Jennifer L. 2014. “Carsharing as Active Transport: What Are the Potential Health Benefits?” *Journal of Transport & Health* 1 (1): 54–62. https://doi.org/10.1016/j.jth.2013.07.003.

Kidd, Alison, and Peter Williams. 2009. “Talybont Energy – Electric Bike Trial Report.” https://talybontenergy.files.wordpress.com/2015/01/ebiketrialreport.pdf.

Kroesen, Maarten. 2017. “To What Extent Do E-Bikes Substitute Travel by Other Modes? Evidence from the Netherlands.” *Transportation Research Part D: Transport and Environment* 53 (June): 377–87. https://doi.org/10.1016/j.trd.2017.04.036.

Le Gouais, Anna, Jenna R. Panter, Andy Cope, Jane E. Powell, Emma L. Bird, James Woodcock, David Ogilvie, and Louise Foley. 2021. “A Natural Experimental Study of New Walking and Cycling Infrastructure across the United Kingdom: The Connect2 Programme.” *Journal of Transport & Health* 20 (March): 100968. https://doi.org/10.1016/j.jth.2020.100968.

Lehner, Stephan, and Stefanie Peer. 2019. “The Price Elasticity of Parking: A Meta-Analysis.” *Transportation Research Part A: Policy and Practice* 121 (March): 177–91. https://doi.org/10.1016/j.tra.2019.01.014.

Liftshare. 2023. “Car Share with Trusted, Reviewed and Rated Liftshare.Com Members.” *Liftshare*. https://liftshare.com/uk.

Matas, A and Raymond, J. L. 2003. “Demand Elasticity on Tolled Motorways.” *Journal of Transportation and Statistics* 6 (2–3): 91–108.

Matas, Anna. 2004. “Demand and Revenue Implications of an Integrated Public Transport Policy: The Case of Madrid.” *Transport Reviews* 24 (2): 195–217. https://doi.org/10.1080/0144164032000107223.

Matas, Anna, Josep-Lluis Raymond, and Adriana Ruiz. 2020. “Economic and Distributional Effects of Different Fare Schemes: Evidence from the Metropolitan Region of Barcelona.” *Transportation Research Part A: Policy and Practice* 138 (August): 1–14. https://doi.org/10.1016/j.tra.2020.05.014.

Matthews, H. Scott, and Eric Williams. 2005. “Telework Adoption and Energy Use in Building and Transport Sectors in the United States and Japan.” *Journal of Infrastructure Systems* 11 (1): 21–30. https://doi.org/10.1061/(ASCE)1076-0342(2005)11:1(21).

Mölenberg, Famke J. M., Jenna Panter, Alex Burdorf, and Frank J. van Lenthe. 2019. “A Systematic Review of the Effect of Infrastructural Interventions to Promote Cycling: Strengthening Causal Inference from Observational Data.” *International Journal of Behavioral Nutrition and Physical Activity* 16 (1): 93. https://doi.org/10.1186/s12966-019-0850-1.

Morgan, Malcolm, and Robin Lovelace. 2022. “NTEM2OD.” Institute for Transport Studies. https://github.com/ITSLeeds/NTEM2OD.
Nightingale, Glenna F., Andrew James Williams, Ruth F. Hunter, James Woodcock, Kieran Turner, Claire L. Cleland, Graham Baker, et al. 2021. “Evaluating the Citywide Edinburgh 20mph Speed Limit Intervention Effects on Traffic Speed and Volume: A Pre-Post Observational Evaluation.” Edited by Sergio A. Useche. *PLOS ONE* 16 (12): e0261383. https://doi.org/10.1371/journal.pone.0261383.
Nijland, Hans, and Jordy van Meerkerk. 2017. “Mobility and Environmental Impacts of Car Sharing in the Netherlands.” *Environmental Innovation and Societal Transitions* 23 (June): 84–91. https://doi.org/10.1016/j.eist.2017.02.001.
Office for National Statistics. 2021. “Business and Individual Attitudes towards the Future of Homeworking, UK - Office for National Statistics.” https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/businessandindividualattitudestowardsthefutureofhomeworkinguk/apriltomay2021.
Olszewski, Piotr, and Litian Xie. 2005. “Modelling the Effects of Road Pricing on Traffic in Singapore.” *Transportation Research Part A: Policy and Practice* 39 (7–9): 755–72. https://doi.org/10.1016/j.tra.2005.02.015.
Perez-Prada, Fiamma, and Andres Monzon. 2017. “Ex-Post Environmental and Traffic Assessment of a Speed Reduction Strategy in Madrid’s Inner Ring-Road.” *Journal of Transport Geography* 58 (January): 256–68. https://doi.org/10.1016/j.jtrangeo.2016.12.018.
Potter, Stephen. 2010. “Transport Integration - An Impossible Dream?” In . University of Plymouth.
Potter, Stephen, and Martin J Skinner. 2000. “On Transport Integration: A Contribution to Better Understanding.” *Futures* 32 (3–4): 275–87. https://doi.org/10.1016/S0016-3287(99)00097-X.
Prager, Fynnwin, Garrett Asay, Bumsoo Lee, and von Winterfeldt. 2011. “Exploring Reductions in London Underground Passenger Journeys Following the July 2005 Bombings.” *Risk Analysis* 31: 773–86. https://doi.org/10.1111/j.1539-6924.2010.01555.x.
Pritchard, Ray, Dominik Bucher, and Yngve Frøyen. 2019. “Does New Bicycle Infrastructure Result in New or Rerouted Bicyclists? A Longitudinal GPS Study in Oslo.” *Journal of Transport Geography* 77 (May): 113–25. https://doi.org/10.1016/j.jtrangeo.2019.05.005.
Romero, Fernando, Juan Gomez, Thais Rangel, and José Manuel Vassallo. 2019. “Impact of Restrictions to Tackle High Pollution Episodes in Madrid: Modal Share Change in Commuting Corridors.” *Transportation Research Part D: Transport and Environment* 77 (December): 77–91. https://doi.org/10.1016/j.trd.2019.10.021.
Santos, Georgina, Hannah Behrendt, and Alexander Teytelboym. 2010. “Part II: Policy Instruments for Sustainable Road Transport.” *Research in Transportation Economics* 28 (1): 46–91. https://doi.org/10.1016/j.retrec.2010.03.002.
Shaheen, Susan A., Mark A. Mallery, and Karla J. Kingsley. 2012. “Personal Vehicle Sharing Services in North America.” *Research in Transportation Business & Management* 3 (August): 71–81. https://doi.org/10.1016/j.rtbm.2012.04.005.
Shewmake, Sharon. 2012a. “The Impact of High Occupancy Vehicle Lanes on Vehicle Miles Travelled.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1986503.
———. 2012b. “Can Carpooling Clear the Road and Clean the Air?: Evidence from the Literature on the Impact of HOV Lanes on VMT and Air Pollution.” *Journal of Planning Literature* 27 (4): 363–74. https://doi.org/10.1177/0885412212451028.
Söderberg f.k.a. Andersson, Alfred, Emeli Adell, and Lena Winslott Hiselius. 2021. “What Is the Substitution Effect of E-Bikes? A Randomised Controlled Trial.” *Transportation Research Part D: Transport and Environment* 90 (January): 102648. https://doi.org/10.1016/j.trd.2020.102648.

Song, Yena, John Preston, and David Ogilvie. 2017. “New Walking and Cycling Infrastructure and Modal Shift in the UK: A Quasi-Experimental Panel Study.” *Transportation Research Part A: Policy and Practice* 95 (January): 320–33. https://doi.org/10.1016/j.tra.2016.11.017.

Stefaniec, Agnieszka, William Brazil, Warren Whitney, and Brian Caulfield. 2022. “Desire to Work from Home: Results of an Irish Study.” *Journal of Transport Geography* 104 (October): 103416. https://doi.org/10.1016/j.jtrangeo.2022.103416.

Sun, Qi, Tao Feng, Astrid Kemperman, and Andreas Spahn. 2020. “Modal Shift Implications of E-Bike Use in the Netherlands: Moving towards Sustainability?” *Transportation Research Part D: Transport and Environment* 78 (January): 102202. https://doi.org/10.1016/j.trd.2019.102202.

Thomas, F, J Klosser, P Mitchell, and G Davies. 2021. “Working from Home Policy and Practice Review – a Research Note.” Waka Kotahi NZ Transport Agency. https://www.nzta.govt.nz/assets/resources/research/research-notes/001/001-working-from-home-policy-and-practice-review.pdf.

Transport for London. 2014. “Drivers of Demand for Travel in London: A Review of Trends in Travel Demand and Their Causes.” https://content.tfl.gov.uk/drivers-of-demand-for-travel-in-london.pdf.

———. 2018. “Segregated Cycling Infrastructure: Understanding Cycling Levels, Traffic Impacts, and Public and Business Attitudes.” https://content.tfl.gov.uk/segregated-cycling-infrastructure-evidence-pack.pdf.

———. 2023. “Economic Benefits of Walking and Cycling.” *Transport for London*. https://www.tfl.gov.uk/corporate/publications-and-reports/economic-benefits-of-walking-and-cycling.

Turner, Mark, and Ruth Wilson. 2010. “Smart and Integrated Ticketing in the UK: Piecing Together the Jigsaw.” *Computer Law & Security Review* 26 (2): 170–77. https://doi.org/10.1016/j.clsr.2010.01.015.

UK Commission for Integrated Transport. 2007. “Physical Integration Chapter 2: Non-Physical Measures To Encourage Integration.” June 7, 2007. http://web.archive.org/web/20070607002442/http://www.cfit.gov.uk/docs/2000/physical/physical/02.htm.

Victoria Transport Policy Institute. 2019. “Telework: Using Telecommunications to Substitute for Physical Travel.” In *TDM Encyclopedia*. Victoria Transport Policy Institute. https://vtpi.org/tdm/tdm43.htm.

Vis, A.A., A. Dijkstra, and M. Slop. 1992. “Safety Effects of 30 Km/h Zones in the Netherlands.” *Accident Analysis & Prevention* 24 (1): 75–86. https://doi.org/10.1016/0001-4575(92)90074-S.

Volker, Jamey M. B. and Handy, Susan L. 2022. “Updating the Induced Travel Calculator: A Research Report from the National Center for Sustainable Transportation,” September. https://doi.org/10.7922/G2P55KTX.

Wardlaw, Malcolm J. 2014. “History, Risk, Infrastructure: Perspectives on Bicycling in the Netherlands and the UK.” *Journal of Transport & Health* 1 (4): 243–50. https://doi.org/10.1016/j.jth.2014.09.015.

Wardman, Mark. 2022a. “Meta-Analysis of British Time-Related Demand Elasticity Evidence: An Update.” *Transportation Research Part A: Policy and Practice* 157 (March): 198–214. https://doi.org/10.1016/j.tra.2022.02.001.

———. 2022b. “Meta-Analysis of Price Elasticities of Travel Demand in Great Britain: Update and Extension.” *Transportation Research Part A: Policy and Practice* 158 (April): 1–18. https://doi.org/10.1016/j.tra.2022.01.020.

Wardman, Mark, Jeremy Toner, Nils Fearnley, Stefan Flügel, and Marit Killi. 2018. "Review and Meta-Analysis of Inter-Modal Cross-Elasticity Evidence." *Transportation Research Part A: Policy and Practice* 118 (December): 662–81. https://doi.org/10.1016/j.tra.2018.10.002.

What Works Centre for Local Economic Growth. 2016. "Transport Toolkit – Integrated Ticketing." Evidence Toolkits. https://whatworksgrowth.org/wp-content/uploads/16-07-18_Integrated_Ticketing.pdf.

———. 2020. "Local Green Investment." https://whatworksgrowth.org/wp-content/uploads/Local_green_investment.pdf.

Wikipedia. 2023. "London Congestion Charge." Wikipedia. February 6, 2023. https://en.wikipedia.org/w/index.php?title=London_congestion_charge&oldid=1137748996.

Wilmink, A. and Hartman, J. B. 1987. "Evaluation of the Delft Bicycle Network Plan: Final Summary Report." The Hague, Netherlands: Ministry of Transport and Public Works. https://www.cycling-embassy.org.uk/sites/cycling-embassy.org.uk/files/documents/evaluation-of-the-delft-bicycle-network-plan-final-summary-report.pdf.

Wiseman, Yair. 2019. "High Occupancy Vehicle Lanes Are an Expected Failure." *International Journal of Control and Automation* 12 (11): 21–32. https://doi.org/10.33832/ijca.2019.12.11.03.