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Research paper

Competition and substitution between public transport modes

Nils Fearnley^{a,*}, Graham Currie^b, Stefan Flügel^a, Fredrik A. Gregersen^a, Marit Killi^a,
Jeremy Toner^c, Mark Wardman^d^a Institute of Transport Economics, Gaustadalleen 21, 0349, Oslo, Norway^b Monash University, Department of Civil Engineering, Clayton, Victoria, 3168, Australia^c Institute for Transport Studies, University of Leeds, Leeds, LS2 9JT, United Kingdom^d SYSTRA, Manchester, United Kingdom

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ABSTRACT

The management and understanding of modal split between public transport (PT) modes is of interest for numerous reasons. It may, for example, be desirable to stimulate passengers to switch from crowded buses and over to higher capacity rail. This requires a good understanding of drivers of transit modal substitution.

The evidence put forward in this paper is based on more than 150 empirically estimated cross elasticities between PT modes from over 20 sources collected from Australia, Europe and USA. These sources include scientifically published evidence as well as grey literature.

This evidence is coded into a database from which our paper presents and analyses the available cross-PT-modal demand relations. We focus on evidence for how fares, travel time and service intervals on PT 'mode A' affect the demand for PT 'mode B'.

Despite generally low levels of substitution between PT modes, passengers are particularly sensitive to in-vehicle, access/egress and waiting time in choosing PT mode and less so for fare variations. In general, rail demand is less sensitive to changes in bus than bus demand is to changes in rail. We also find that peak-hour demand more markedly switches between PT modes than off-peak demand does.

1. Introduction

Within public transport (PT) systems there may, for various reasons, be of interest to better understand the dynamics of demand between PT modes, for example what happens to bus demand when metro services improve. Such knowledge may guide policymakers who seek to shift passenger flows away from overcrowded buses and onto higher capacity rail modes, as in Oslo (Ruter, 2015) or the other way round to encourage shifts from crowded metro systems and over to buses, which may be a goal for transit systems like London's (BBC, 2006; Grayling & Glaister, 2000). The planning for and handling of unplanned disruptions and strikes would also benefit from improved knowledge of modal substitution between PT modes (Nguyen-Phuoc, Currie, De Gruyter, & Young, 2017a; Nguyen-Phuoc, Currie, De Gruyter, & Young, 2017b). On a higher level, better understanding of the level and aspects of competition between PT modes can help improve competition legislation and inform the many countries that still protect their heavy rail lines from competition with express coaches (Aarhaug & Fearnley, 2016;

Augustin, Gerike, Sanchez, & Ayala, 2014; Beria, Grimaldi, Debernardi, Ferrara, & Laurino, 2014; Van de Velde, 2009; Walter, Haunerland, & Moll, 2011). In deregulated PT markets with free entry, evidence of key dimensions of intra-PT modal competition would be a competitive advantage for incumbents and potential entrants alike.

A key indicator of competition between PT modes is the cross elasticity of demand (hereafter ϵ_{ij}), which is the demand effect on mode i when an attribute of mode j is changed marginally – for example the effect on demand for bus with respect to metro fares; if this cross elasticity of demand is, for example 0.2, one would expect that a 1 percent increase in metro fares increases bus demand by 0.2 percent.

Cross elasticities of demand are relevant, although controversial,¹ indicators of competition also in the legal sense of competition law. In order for competition regulators and courts to define the 'relevant market', evidence of cross-price elasticities is sometimes used to support SSNIP test (Small but Significant Non-transitory Increase in Price).

Following Dodgson (1986) and provided that PT modes are substitutes, cross-elasticities of demand, ϵ_{ij} , depend crucially on 1) own-

* Corresponding author.

E-mail address: naf@toi.no (N. Fearnley).¹ The 'cellophane fallacy' case (US Supreme Court, 1956) is regarded a famous case of erroneous use of cross-price elasticity evidence when defining market power and 'relevant market'<https://doi.org/10.1016/j.retrec.2018.05.005>

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elasticity of demand, ϵ_{ij} ; 2) the two modes' relative market shares, Q_j/Q_i ; and 3) diversion factors, δ_{ji} , which is a relative measure of the demand change in mode i compared to the demand change of mode j . The relationship can be written as,

$$\epsilon_{ij} = |\epsilon_{ij}| \frac{Q_j}{Q_i} \delta_{ji} \quad (1)$$

It is clear from this formula that the cross-elasticity of demand for mode i with respect to an attribute of mode j is larger the larger mode j 's own elasticity is, the larger market share mode j has relative to mode i , and the higher diversion is from mode j to mode i .

The relative market shares and the diversion factor will typically differ considerably between areas (see, e.g. [Dunkerley, Wardman, Rohr, & Fearnley, forthcoming](#)). Even *within* areas there may be large differences depending on, e.g., trip purpose, time of day, detailed location relative to various PT modes' stops and stations, and so on. It follows that cross elasticities of demand are particularly context dependent, and much more so than own-elasticities of demand whose levels show a remarkably high level of stability.²

[Fig. 1](#) shows the relative share of transit modes in world cities and also for world regions of cities, drawing on data from [UITP \(2001;2015\)](#). In cities at the top of the figures, bus totally dominates over other PT modes. Here, a shift of only a small percentage of passengers from bus over to other PT modes would represent a large percentage increase in those other PT modes. At the bottom end of the figures, where bus has a relative minor role, the transfer of the same small percentage bus passengers over to other PT modes would represent a far less increase on those PT modes. This illustrates quite well the importance of context when analysing cross elasticities of demand.

1.1. World cities

While [Dodgson's](#) cross-elasticity formulation in [equation \(1\)](#) relies on deduction based on known (or assumed) parameters, the general specification of cross-elasticity of demand, assuming demand for mode i is a differentiable function of an attribute (P) of mode j , is,

$$\epsilon_{ij} = \frac{dQ_i}{dP_j} \frac{P_j}{Q_i} \quad (2)$$

The demand elasticities literature draws a line between “conditional” and “unconditional” demand elasticities ([Balcombe et al., 2004](#)). “Conditional” means that the elasticity estimate is conditional upon a similar attribute change across all those attributes. E.g. all fares change by $X\%$ (and not just the price of one ticket type, like the single ticket price), or alternatively that all PT fares in an area change by the same percentage (and not just of one of the PT modes). “Unconditional” elasticity estimates, on the other hand relax this assumption and implies that a change in an attribute (e.g. price of monthly travel card) can be the only change (other ticket prices do not change) taking place. Since the barriers to switching between ticket types or, to some extent, between PT modes are typically regarded as less strong than barriers to switching to/from non-PT modes (or not travel), the general expectation is for unconditional elasticities to be larger, in absolute terms, than conditional elasticities. A big increase in, say, the single ticket price will typically lead to large change in market shares of different ticket types, i.e. a large unconditional demand elasticity, but have less effect on overall PT demand. Most usually in the own-elasticity literature, elasticities of demand refer to changes that are conditional upon an attribute change of the same magnitude that applies to all PT modes or fare types. However, and in contrast to this, the focus in this paper is largely

² For example, the UK recommended own-price elasticity of demand for bus changed from -0.3 to -0.4 between 1980 and 2004 ([Balcombe et al., 2004](#); [Webster and Bly, 1980](#)). The Norwegian recommended value is -0.4 ([Norheim & Ruud, 2007](#)) and [Litman \(2017\)](#) global review concludes that short run transit fare elasticities are typically in the region of -0.2 to -0.5 .

on unconditional elasticities, since cross-elasticity of demand between PT modes by definition relies on changes in attributes of one PT mode only.

Based on this background, the purpose of this paper is to present and analyse existing evidence of cross elasticities of demand between PT modes in particular in urban areas. In doing so, we seek to lay the foundation for improved understanding of the dynamics of demand between different PT modes. The potential benefits and beneficiaries of this paper are many, as described above, although this paper is primarily motivated by a genuine curiosity and a deep interest in passenger transport demand, which these co-authors have shared for years (see, e.g., [Fearnley et al., 2017](#)).

When studying cross elasticities of demand between PT modes, there is an obvious question whether in fact PT modes operate parallel routes in such a way that there occurs real competition between them. There is great variation between cities and countries in this respect. The ‘traditional’ planning paradigm would oppose operations of parallel services, e.g. of bus and rail, so as to minimise cannibalism and to promote the different modes' scale economies. Such duplication of expensive resources would be regarded as wasteful. From this perspective, different PT modes serve different markets and competition between those modes is very limited. An alternative view would be that in any sizable city with more than one PT mode in operation with a reasonable service network, there would usually be several alternative PT routes and modes between most OD pairs and therefore there may be considerable competition between those PT modes and routes. A typical example would be transit services between a city centre and its airport. Additionally, different public transport modes may offer different trade-offs between service attributes (e.g. time and money), such that if travellers have different preferences, it may even be efficient to run parallel services with different service attributes. From this perspective, it is of relevance to investigate outcomes of changes to one of the alternative PT modes on all other PT modes.

The remainder of this paper is organised as follows. [Section 2](#) describes the process of identifying data and provides an overview of the sources of evidence that goes into the analysis. [Section 3](#) presents and analyses the data, while [section 4](#) discusses the findings and draws conclusions and their policy implications.

2. Method and data

This review brings together evidence from a wide range of sources. The library search includes resources such as ISI, Google Scholar, World Transit Research database, Bureau of Infrastructure, Transport and Regional Economics (BITRE) Elasticities Database Online, Springer Link, ScienceDirect, and Tylor and Francis Online. Search terms typically consisted of combinations of (transport* or travel or passenger), cross, elasticit*, demand, (transit or bus or public transport or rail or tram or metro or LRT or BRT), (urban or city or local), and so on. Additionally, we contacted, directly, a number of colleagues across the globe, who were considered likely to either hold unpublished material or to help us point to important pieces of work in this area.

This exercise resulted in the identification of 20 different sources of literature. Of these, 15 were primary sources and 5 secondary (cited) sources. From this sample of 20 references, 174 different cross-elasticity estimates between PT modes are recorded. To our knowledge, this is the largest data set of cross elasticity evidence between public transport modes ever assembled and analysed. Although our focus is on local transit, we included a few notable contributions that refer to intercity transport and longer distance trips. Each source has been coded into a spreadsheet table with information about location, year, study type, data type, method, estimated cross elasticity estimate, and so on.

As demonstrated in [equation \(1\)](#), the relative market share, $\frac{Q_j}{Q_i}$, is

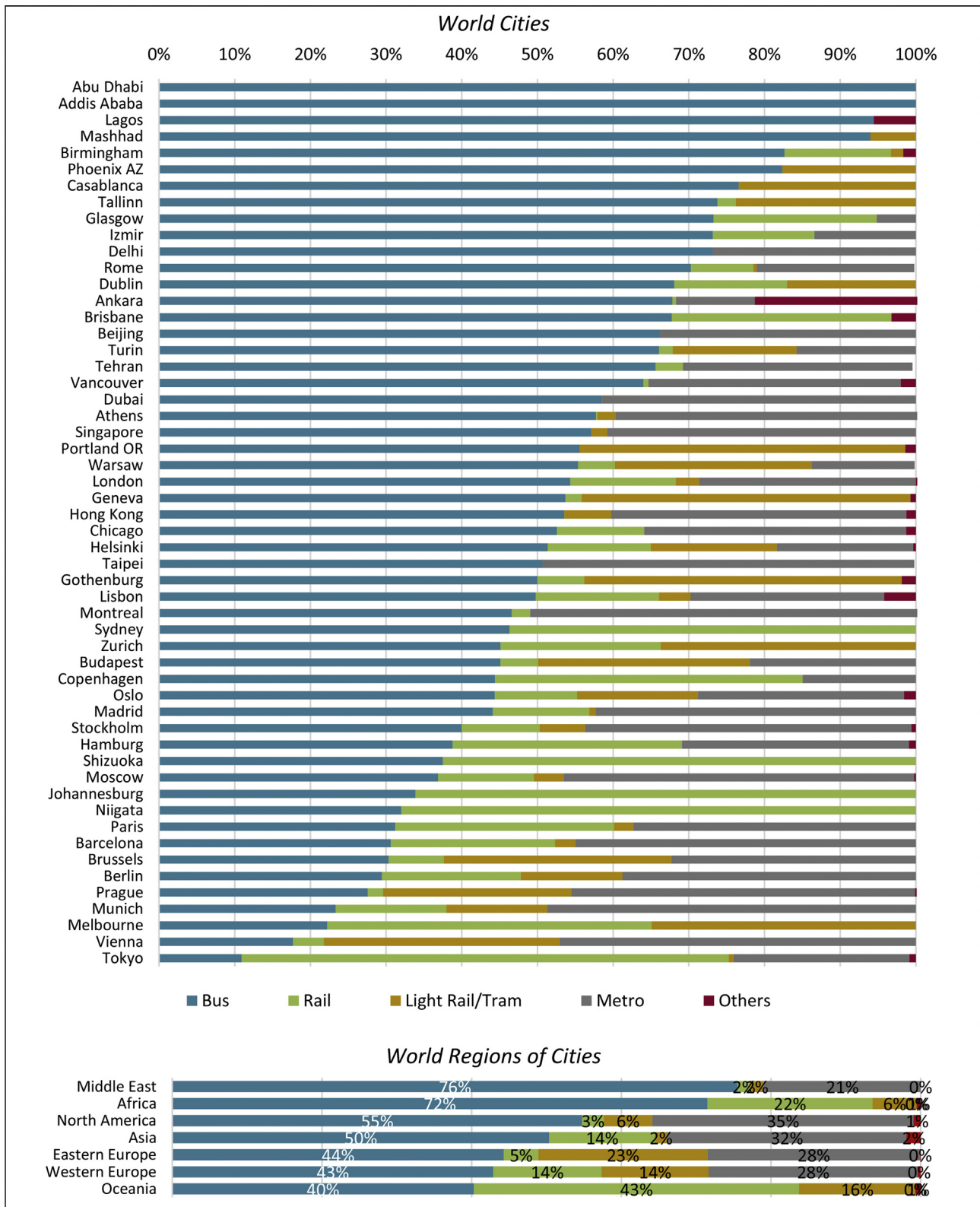


Fig. 1. Transit Mode Share of Total Transit Demand in Selected World Cities and for World Regions of Cities. Source: Analysis of UITP 2001, 2015 data.

highly significant explainer of cross-elasticity results. Much effort has therefore been invested in this variable during data collection. For 124 observations (71% of the total), relative market shares were in fact reported in the cited sources. For the remaining observations, we first contacted corresponding authors. This yielded another 31 observations (18%) of market shares from a first source. Four more relative market

shares (2%) were retrieved from EPOMM's Modal Split Details³ and Australian Government's Bureau of Infrastructure, Transport and Regional Economics' (BITRE) Urban passenger transport statistics. For the

³ http://www.epomm.eu/tems/result_cities.phtml?more=1.

Table 1

References in database and cross-PT-modal relations covered. (Demand for first mentioned mode with respect to last mode. E.g. “bus-rail” means demand for bus with respect to change in a rail attribute.)

Reference No. and source	Demand relations covered
1. Dargay, Clark, Johnson, Toner, and Wardman (2010)	Bus-rail; rail-bus
2. Dargay (2010)	Bus-rail; rail-bus
3. Douglas, Franzmann, and Frost (2003)	Bus-rail; rail-bus
4. Fairhurst and Morris (1975)	LRT-bus
5. Flügel, Caspersen, Angell, Fearnley, and Kwong (2015)	Bus-rail; LRT/metro-bus; LRT/metro-rail; rail-LRT/metro; bus-LRT
6. Glaister and Lewis (1997)	Bus-rail; LRT-bus; bus-LRT
7. Mackett and Bird (1989)	Bus-rail
8. Mc Fadden (1974)	Bus-rail; rail-bus; LRT-bus
9. MVA (1996)	Bus-rail; rail-bus
10. MVA (2008)	Rail-bus
11. Oscar Faber TPA (1993)	Bus-rail; rail-bus
12. Rich and Mabit (2011)	Bus-rail; rail-bus
13. Rohr et al. (2013)	Bus-rail
14. Steer Davies Gleave (1996)	Bus-rail; metro-rail; bus-metro; metro-bus
15. Talvitie (1973, cited in Lago et al. 1981)	Bus-rail; rail-bus
16. Taplin, Hensher, and Smith (1999)	Bus-rail; rail-bus
17. Toner and Wardman (1993)	Bus-rail; rail-bus
18. Wardman (1993)	Rail-bus
19. Wardman (1992)	Rail-bus
20. Wardman and Whelan (1995)	Rail-bus

remaining 15 observations (9%), an expert inquiry was undertaken, in which three of the co-authors and two external experts provided their educated guestimate of market shares for the two modes in question for each cross-elasticity estimate, based on the available background information (year, location, trip purpose, etc.). For each of these guestimates the experts would indicate the certainty of their guestimate. This certainty score was used to calculate weighted average likely mode shares for each observation.

Table 1 presents the 20 sources and which cross elasticity relations they cover, while Table 2 presents some key characteristics of these sources.

3. Empirical evidence and meta-analysis

3.1. Overall tendencies

Table 3 shows the assembled values for internal transit mode cross elasticities under the separate policy change headings of fares, in-vehicle journey time, wait time, access/egress time and number of interchanges. Values shown are the average of cross elasticity evidence assembled with min/max values also shown. Sub-section 3.2 provides a statistical analysis of these observations, and performs significance tests.

Table 2

Characteristics of sample, N = 20. “na” typically refers to secondary sources.

Publication type	6 published report; 5 journal/book; 4 unpublished academic; 2 conference paper; 2 thesis; 1 other
Country/region covered	13 UK/GB; 1 Norway; 2 Australia; 2 USA; 1 Scotland; 1 Europe
General method	9 predicting with choice model; 4 regression model; 2 deduced; 2 transport model; 3 other/na
RP/SP	12 RP; 3 SP; 3 RP-SP; 2 other/na
Type of data	9 cross sectional; 4 time series; 3 pseudo panel/SP; 4 other/na
Level	4 national; 9 urban; 1 international; 2 station-to-station flow; 4 other/na
Location	9 urban; 7 interurban; 4 long distance
Year of publication	3 before 1980; 1 1980–89; 9 1990–99; 2 2000–09; 5 2010 and later

Some 174 separate values were assembled. Most (76) related to fare change evidence followed by cases where in-vehicle travel time had been adjusted (53). Most evidence concerned changes in transit modes which affected rail demand (80) and bus demand (78). Few cases of metro and light rail demand impacts have been documented. Metro cases only considered changes in fares between transit modes.

All values in Table 3 are positive as would be expected, since all attributes in question are ‘bads’ (cost, time, interchanges, hassle). It means that an increase in these attributes for one PT mode will, all else equal, make it less attractive and thereby increase demand for other PT modes.

Average transit cross elasticity values ranged from a minimum of 0.01 to a maximum of 0.48. The highest average value of 0.48 was for bus demand impacted by changes in in-vehicle journey time by rail. The implication is that, all other things being equal, a 10% reduction in journey time by rail would act to reduce bus demand by 4.8%. The second highest average value is 0.38 for bus demand being impacted by changes in access/egress and transfer time on light rail. The implication is a 10% reduction in light rail access/egress and transfer time would reduce bus demand by 3.8%.

In general, rail demand is less elastic (or stickier) to changes in bus than bus demand is to changes in rail. For example, a 10% fare decrease on rail relative to bus decreases bus demand by 2.8% ($\epsilon_{ij} = 0.28$) while a 10% relative decrease in fares by bus acts to decrease rail demand by only 1.5% ($\epsilon_{ij} = 0.15$). This pattern is apparent for almost all policy variables. Interestingly it does not follow for the number of interchanges; $\epsilon_{ij} = 0.03$ for the number of rail interchanges impacting on bus demand, but is a massive 0.24 for bus impacting on rail demand. The implication is that a 10% decrease in the number of interchanges by rail acts to decrease bus demand by 0.3% but a 10% decrease in bus interchange acts to decrease rail demand by 2.4%. However, only a single set of data points is behind this evidence so this result must be taken with a good degree of caution.

The lowest average cross elasticity values in Table 3 concern changes in policy variables for rail and their impact on light rail (fares, in-vehicle journey time, wait time and interchanges) and for changes in light rail wait time impacting rail demand. We can conclude from this that heavy and light rail system demands are relatively insensitive to each other while bus demand is much more sensitive to rail and heavy rail. Metro is also quite insensitive to rail but again there is not much evidence to go on from available sources.

By mode, bus demand is most sensitive to rail in-vehicle travel time ($\epsilon_{ij} = 0.48$), light rail access/egress/transfer time ($\epsilon_{ij} = 0.38$) and rail wait time ($\epsilon_{ij} = 0.22$). Bus demand is most insensitive to rail interchange ($\epsilon_{ij} = 0.03$) and light rail wait time ($\epsilon_{ij} = 0.05$). However, for all low values of elasticities there are commonly few data points.

Rail demand is most sensitive to bus in-vehicle time ($\epsilon_{ij} = 0.26$), bus interchange ($\epsilon_{ij} = 0.24$) followed by bus fare ($\epsilon_{ij} = 0.15$). Rail demand is least sensitive to light rail wait time ($\epsilon_{ij} = 0.01$), light rail fare ($\epsilon_{ij} = 0.02$) followed by light rail interchange and in-vehicle time ($\epsilon_{ij} = 0.06$).

Light rail demand is most sensitive to bus interchange ($\epsilon_{ij} = 0.23$) and bus fare ($\epsilon_{ij} = 0.21$) followed by bus in-vehicle time ($\epsilon_{ij} = 0.15$). Light rail demand is less sensitive to almost all rail based policy measures. However, for all light rail demand related values except bus fare, there is only a single point of evidence for each case.

Metro demand data is only available for changes in bus and rail fares. Metro demand is most sensitive to bus fare ($\epsilon_{ij} = 0.21$) and least to rail fare (0.10) however again there are only single data points of evidence available for each case.

The minimum and maximum values in Table 3 illustrate the range of values found in the review. The highest maximum values found are above 1.00 and all relate to bus demand affected by changes in rail fares ($\epsilon_{ij} \text{ max} = 1.31$), rail in-vehicle travel time ($\epsilon_{ij} \text{ max} = 1.09$) and rail wait time ($\epsilon_{ij} \text{ max} = 1.00$). Maximum values of this scale emphasise how bus demand is sensitive to changes rail design but again caution is warranted since only a few data points are available in the evidence;

Table 3
Summary of internal cross-modal transit elasticities assembled from the research literature & practice review.

Demand for	With respect to	Change in Policy Variable																			
		Fare				VT/journey time				Wait time headway				Access/egress/transfer time				No. of interchanges			
		N	Mean	Min	Max	N	Mean	Min	Max	N	Mean	Min	Max	N	Mean	Min	Max	N	Mean	Min	Max
Light rail	Bus	5	0.21	0.11	0.28	1	0.15	0.15	0.15	1	0.06	0.06	0.06	1	0.03	0.03	0.03	1	0.23	0.23	0.23
	Rail	1	0.01	0.01	0.01	1	0.01	0.01	0.01	1	0.01	0.01	0.01	1	0.06	0.06	0.06	1	0.01	0.01	0.01
Bus	Light rail	3	0.16	0.10	0.25	1	0.15	0.15	0.15	1	0.05	0.05	0.05	2	0.38	0.38	0.38	1	0.17	0.17	0.17
	Rail	31	0.28	0.02	1.31	23	0.48	0.03	1.09	9	0.22	0.03	1.00	5	0.15	0.03	0.34	1	0.03	0.03	0.03
	Metro	1	0.16	0.16	0.16																
Rail	Light rail	1	0.02	0.02	0.02	1	0.06	0.06	0.06	1	0.01	0.01	0.01	2	0.11	0.11	0.11	1	0.06	0.06	0.06
	Bus	32	0.15	0.01	0.49	26	0.26	0.02	0.91	12	0.08	0.03	0.18	3	0.13	0.04	0.25	1	0.24	0.24	0.24
Metro	Bus	1	0.21	0.21	0.21																
	Rail	1	0.10	0.10	0.10																

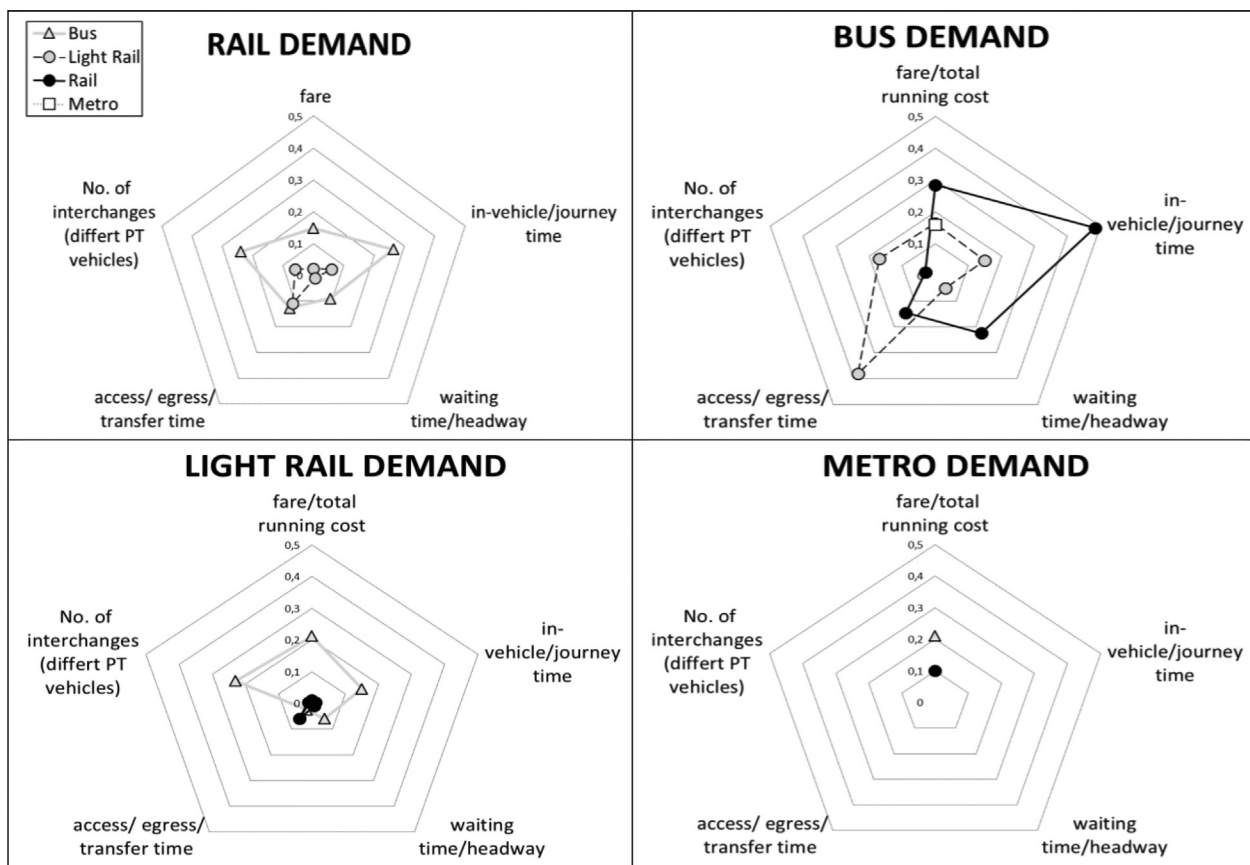


Fig. 2. Average Internal Transit Cross Modal Elasticities - Mode Affected and Mode Changed – 5 types of policy change.

values of this scale certainly represent extremes of experience – e.g. caused by extreme relative market shares.

Fig. 2 illustrates the relative average values of cross modal internal transit elasticities by mode of demand affected (rail, bus, light rail and metro). This illustrates the imbalance of changes in rail based modes on bus demand vs changes in bus on rail demand; bus demand has the highest cross elasticities notably for rail in-vehicle time as related above. Bus demand is also highly sensitive to light rail access/egress and transfer time. Rail demand is more influenced by bus in-vehicle time and the number of interchanges. Light rail demand is more influenced by the number of bus interchanges. All other patterns have quite small cross modal elasticity effects ($\epsilon_{ij} < 0.2$).

3.2. Statistical analysis

In this section, we present a regression model on the cross-elasticities identified in the literature study, i.e. we perform a formal meta-analysis, a methodological approach that is widely applied in transportation research (Holmgren, 2007; Melo, Graham, & Brage-Ardao, 2013; Wardman, 2014).

The motivation in our case is threefold: 1) we want to test if the general patterns observed and discussed in the previous section are retained after controlling for market shares and the applied method 2) we want to measure the effect and test for statistical significance of factors affecting cross-elasticities 3) we want to present a simple model that may be used to predict cross-elasticities in scenarios where data is

lacking.

Cases involving metro are excluded from this analysis because of the low number of observation regarding that transport mode.

The presented model is mathematically given as:

$$CE = e^{c + \sum_{m=1}^M \beta_m * D_m + \sum_{a=1}^A \beta_a * D_a + \sum_{c=1}^C \beta_c * D_c + \sum_{d=1}^D \beta_d * D_d + \beta_{rms} \ln(RMS) + \epsilon}$$

Where;

- CE > 0 is the cross-elasticity identified by the literature study.
- c is the constant term.
- D_m are dummy variables identifying the mode combination of affected x altered mode. β_m are the corresponding parameters.
- D_a are dummy variables identifying the underlying attribute. β_a are the corresponding parameters.
- D_c are dummy variables identifying the country/continent. β_c are the corresponding parameters.
- D_d are dummy variables identifying the type of dataset (RP, SP or combined RP-SP). β_d are the corresponding parameters.
- RMS > 0 is the relative market share of the altered mode compared to the affected mode This variable is log-transformed which helps interpretation. β_{rms} is the corresponding parameter.
- ε is an IID-normally distributed error term.

The specification as a log-transformed model is supported by tests we performed indicating heteroscedasticity and detected heteroscedasticity. After a log-transformation the model constitutes a linear regression models that can be estimated with the standard least square method. The beta-parameters measure the relative effect (percent change) of the covariate on the cross-elasticity compared to the normalised level. The reference categories are m = Rail × Bus, a = fare, c = Australia, d = RP. Note that e^c (i.e. e to the power of c, or exp(c)) is the cross elasticity of normalised level, provided that the altered and affected mode have the same market shares (RMS = 1). Table 4 presents model estimates.

To ease interpretation of the model, regard a situation where we are interested in predicting the cross-elasticity of changes in train headway on the demand for buses in a (hypothetical) Norwegian study based on SP-data. Assuming the relative market share of train compared to buss to be 0.5, the cross elasticity is then calculated as: e^{-2.433+0.138-0.442-0.0629+0.703+ln(0.5)} = 0.0614

Taking a closer look at the parameter estimates, we see that cross-elasticities between light-rail and train are significantly lower than between rail and bus. This might be intuitive given that light train and train do seldom share the same market (light train seldom operates on long distances) while buss services are a closer substitute to train given that the also operate on longer distances. This is in line with the overall tendency found in the previous section.

The parameter estimates give a strong indication for that in-vehicle time has a stronger demand effect than fares, given the significant positive parameter on the cross-elasticity. The results suggest that in-vehicle time implies a 46,7% higher cross-elasticities than fares. Headway/waiting time yields lower cross-elasticities than fares (and in-vehicle time).

There seems to be an indication for that studies from the UK produce higher estimates compared to Australia (and Europe/Norway). This finding is hard to interpret without going deeper into the material – which is outside of the scope of this paper.

The relative market share has – as expected – a high and statically significant effect on cross-elasticities. A 1% change in this variable leads to 0.459% higher cross-elasticity.

Finally, we find evidence for that SP studies predict the highest cross-elasticities; significantly higher than RP-studies (and combined RP-SP studies). Although the analysis relies on only three studies that use SP data, this is an interesting finding from a methodological point of view and seems to be in line with caveats of using SP studies for

Table 4

Linear regression. Dependent variable: LN(Estimated cross elasticity). “Affected mode × Altered mode” is interpreted as demand for affected mode with respect to an attribute change of the altered mode.

	Coefficient	SE
Affected mode × Altered mode		
Light rail × Bus	0.142	-0.351
Light rail × Rail	-1.442 ^a	-0.466
Bus × Light Rail	0.511	-0.376
Bus × Rail	0.138	-0.174
Rail × Light Rail	-1.117**	-0.454
Rail × Bus	Ref	
Attribute		
Fare	Ref	
In-vehicle/journey time	0.467 ^a	-0.163
Waiting time/headway	-0.442**	-0.217
Access/egress/transfer time	0.245	-0.283
No. of interchanges	0.191	-0.417
Country		
Australia	Ref	
Europe	-0.671	-0.42
Norway	-0.0629	-0.368
US	0.48	-0.382
United Kingdom	0.477**	-0.235
LN(Relative market share)	0.459 ^a	-0.0776
RPSP RP		
RP	Ref	
SP	0.703**	-0.283
Combined	-0.00486	-0.19
Constant	-2.433 ^a	-0.296
Observations	171	
R-squared	0.482	
Adjusted R-squared	0.428	
Log Likelihood	-210.8	

^a p < 0.01; **p < 0.05; *p < 0.1.

demand studies because of the inherent hypothetical bias attached to SP-studies (Hensher & Li, 2010).

4. Discussion and conclusions

Although we are unaware of any review studies or meta-analysis that has gathered the amount of evidence of cross elasticities of demand between transit modes which is presented in this paper, we are still left with a mere 20 references and 174 cross elasticity estimates. This limited amount of evidence is an indication of a knowledge gap, which would be useful to fill. For the purposes of our meta-analysis, however, the main implication of the limited amount of evidence is the fact that, when broken down by different modal pairs and attributes, most cross elasticity relations estimated are based on few observations (N). The only cross elasticity evidence with a considerable amount of evidence (N > 10), refers to combinations between bus and rail and for changes in fares, travel time and headway. For the remaining cross elasticity relations, available evidence is extremely scarce in the literature. This means that the evidence and findings of this paper must be treated with a great amount of caution. Adding to that, cross elasticities are particularly context dependent. Therefore, this compilation of evidence from across the globe brings in additional uncertainty that should be kept in mind, even when the statistical analysis has controlled for contextual variables including study location.

Having regards to these caveats, the review and meta-analysis identifies a few moderately robust insights.

One is that competition between rail and LRT is almost non-existing. Bus, on the other side, appears to compete with both rail on longer trips and light rail on shorter trips. The implication is that, where rail modes seek to attract more passengers (as in Oslo) or where the demand for rail modes is exceeding rail capacity (as may be the case in London), bus is likely the most relevant alternative mode, which passengers

would be diverted from (Oslo) or to (London), respectively.

Another is the fact that travel time seems to be the most important aspect of inter-modal competition, followed by fare, access/egress/transfer time, and number of interchanges. Interestingly, waiting time comes out as the attribute with the lowest cross elasticity, when correcting for other aspects of the study. Although this finding may be uncertain due to few observations, it may be related to the amount each of these attributes add to passengers' Generalised Costs (GC). Since our data primarily refers to urban transport, where service frequencies in general are likely to be high, waiting time may add less to GC than travel time and fares do. The policy implication is to focus on travel time differences between PT modes, if the goal is to shift passengers between PT modes. However, the extent to which travel times are in fact possible to change significantly on a system level, is a question for debate. One may argue that relative prices (i.e. fares) are easier to change, despite their potential political (and budgetary) costs.

A third is related to study area and methods applied. UK studies report much higher cross elasticities than studies from other countries and continents, all else equal, as do stated preference studies. There is not enough information in the data to investigate this further, but future studies should scrutinise these preliminary findings.

Fourth, we find statistical support for the theoretical argument that market shares play important role for the magnitude of cross elasticities. The finding is reassuring and, indeed, it helps cast some confidence on the statistical meta-analysis.

The cross modal internal demand effects presented in this paper are caused by a number of likely influences; these are hypothesised below.

1. **The relative scale of transit mode** – Separate transit modes almost always have a different scale of coverage of cities with bus services generally dominating and light rail and metros representing a smaller share of metropolitan area wide service area coverage and ridership. There are exceptions to this generalisation but in general, bus services tend to dominate at least in spatial network coverage terms in cities. It follows that the scale of change in bus policy measures (fares, level of service etc.) would thus dominate demand effects of rail based modes compared to rail mode effects. However, this only works if bus competes with rail directly for the same market and that they serve similar catchment areas. Regarding this, Flügel, Fearnley, and Toner (2018) found that the number of available travel alternatives each traveller has, significantly affects diversion factors, which again are key determinants of cross-elasticities. In practice, rail is a longer distance mode and bus less so. In our data, rail policy changes tended to have much greater market effects than bus did on rail markets. The implication is that despite bus markets, in general, being bigger, they don't compete for the same market. Hence, rail is somewhat protected from changes in bus policy but bus is more sensitive to changes in rail policy. So there appears to be more to relative market competition than just relative market size.
2. **The relative scale of own mode walk access vs. cross mode feeder transfer demand** – If the market for a transit mode involves almost entirely walk on access/egress then cross elasticity transit elasticities should be smaller than for modes with high shares of ridership making interchanges from other transit modes. While this hypothesis seems logical we doubt there are any clear patterns of ridership in cities where specific modes have more or less inter-transit transfer shares than others. Rail has strong walk on ridership, but bus feeder to and from rail is also dominant in many cities, and this effect would act to influence both bus and rail. We also see no clear patterns in the cross-elasticity results which can prove or disprove this hypothesis. In practice, actual effects will vary in the real world by variations in circumstances between cities.
3. **Effects of near catchment competition between transit modes** – In general, close spatial proximity between the alignments and stops/stations of transit modes should act to increase cross modal market effects. The inverse of this effect is that modes with spatially segregated alignments, located well away from other modes, should have smaller cross modal demand effects. As mentioned in section 1, it is a core principal of integrated network planning of transit systems that transit modes work together to achieve a wider spatial distribution of services and that wasteful competition and overlap of routes is avoided. Key to this principle is that rail modes, due to their high cost, are protected from competition from nearby bus routes. On this basis we might expect rail, light rail and metro demand to display much lower demand elasticities than bus and indeed this is the dominant picture of the results displayed (Table 3 and Fig. 2). Another example of this principle is that light rail and rail in particular are rarely spatially adjacent in the real world due to the high costs of construction and operation. This suggests interaction between rail and light rail markets would be small. This is indeed also supported by the cross-elasticity results presented. However, the real world is a complex place and area-wide network integration has not been achieved in all cities; it also varies in quality within cities. Indeed, commercial competition occurs in places and this might act to dampen the transit mode effects hypothesised above. We also note that 'Force feeding' of ridership to rail (metro and light rail) stations from bus is also undertaken to achieve the same network integration objective and this might act to counteract cross modal effects since as noted above (point 2), cross transit mode feeding can act to increase cross modal demand sensitivity.
4. **Crowding levels affect transit mode choice** – We have already argued that crowding is one possible policy reason for shifting demand from rail to bus – or the other way around. However, crowding directly impacts the generalised cost of different transit modes such that less crowding is more attractive than more crowding. In this way, crowding affects mode choice. All else equal, the less crowded mode would be preferred. Crowding levels of different modes would indeed differ within areas as well as between areas and cities. Ideally, therefore, our studies should have included information about levels of crowding. Unfortunately, this is not the case. Beyond the fact that crowding itself causes modal shift, we can only speculate that, for example, crowding plays a role in causing the high cross elasticities observed in UK studies, where crowding is more of a problem, relative to countries like Norway, where on-board crowding is less of a problem.

Overall, the cross modal internal transit mode elasticities assembled in this research represent one of the first times that this subject has been explored in any depth. There are clearly large gaps in evidence and future research should seek to fill these. While this meta-study has only scratched the surface, it would be useful to explore further the factors causing the variations in patterns of cross transit modal demand effects discovered in future research. A point worth noting for future research is the fact that, as opposed to cross-elasticities, diversion factors are independent of the relative market shares of the altered mode – at least as a first-order effect – and can therefore be expected to be more stable across studies (Wallis, 2004) and more transferable (BAH, 2003). Flügel et al., 2018 produced a scatter-plot which illustrates how cross-elasticities are more influenced by relative market shares than diversion factors are. As a central element to the cross-elasticity equation (1), better understanding of diversion factors stand out as low-hanging, and important, fruit for gaining further insights into cross-modal demand dynamics. Despite the gaps in evidence found in this review it has provided a range of insights into cross transit modal demand effects which should prove of value to planners, policy makers and industry stakeholders into the future.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.retrec.2018.05.005>.

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