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Triggers of Urban Passenger Mode Shift – State of the Art and Model Evidence

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Abstract

Mode shift is at the core of sustainable transport in all world cities; yet we know comparatively little about it. While there is ample evidence of within-mode demand effects, we know in general very little about what mode these new passengers came from. This paper addresses this issue by gathering existing evidence of cross-mode demand interactions (or cross elasticities) from studies conducted worldwide, and by presenting new evidence of cross-mode elasticities from Greater Oslo. We establish the theoretical, methodological and empirical states of the art with respect to demand effects at a system level, i.e. across transport modes. We present and compare empirical evidence and identify the influence of various factors on the variation in the cross elasticities, including context factors and methodological factors. Next, we present new evidence of cross elasticities from a study conducted in Greater Oslo based on 15,000 travel observations. Our model illustrates very well how the same triggers, e.g. the cost of car use, bring about different mode switching effects depending on trip purpose and trip distance. The paper's combination of consolidated evidence and new evidence from our own empirical study forms the basis for recommendations to urban policymakers whose goal is to obtain modal shift.

Selection and peer-review under responsibility of Association for European Transport.

Keywords: passenger transport; demand; cross-elasticity; modal shift

Selection and peer-review under responsibility of Association for European Transport.

1. Introduction

Mode shift is at the core of sustainable transport in all world cities; yet we know little about its triggers and how policies targeting one transport mode affects the demand for another. The question is of course critical for policies that are motivated by a need to change mode shares, e.g. in favour of more environmentally friendly modes. And it is particularly so for the design of 'carrot' measures, like improving public transport in order to reduce car use. It is not sufficient to know within-mode demand effects, like the patronage increase effect of bus service improvements. The increase in bus patronage may well come from generated traffic, walking or cycling and not from motorists who switch mode, counter to the intended effect. Fearnley (2013) shows, for example, that free public transport is sometimes promoted as a means to reduce car traffic, while in fact it has often negligible effect on car traffic, but attracts pedestrians and bicyclists and increases total transport emissions. Better understanding of inter-modal dynamics would clearly help identify more effective policies.

The change in demand that follows a change in a transport mode's attribute is commonly termed a demand elasticity, which is a measurement of how sensitive demand is to that attribute (see, e.g. Balcombe et al., 2004; Litman 2017). For example, a price elasticity of -0.4 means that a price increase of 1 % reduces demand by 0.4 %, all else being equal. The concept of demand elasticities is well established and widely studied. These elasticity estimates are useful in many respects, including assessment of demand and revenue effects of policy options.

However, given this wide focus of demand elasticities, the scientific literature is almost entirely concerned with own-elasticities, i.e., the effects on demand for mode i when an attribute of mode i is changed. Much less attention is paid to cross-elasticities, which are the demand effects on mode i when an attribute of mode j is changed. While cross-elasticities of demand are rarely presented in the research literature, reviews of cross-elasticities are even rarer. Wardman (1997), TRACE (1999) and BAH (2003) can be said to be notable exceptions, although they are limited in scope and coverage. TRACE (1999) collected evidence of how car policies (fuel price, travel time, road pricing and parking charges) affect public transport demand. Wardman (1997), whose focus on inter-urban transport, concludes that, given the wide variation in choice model cross-elasticity estimates, they are neither easily transferable nor particularly reliable as standalone estimates. Also BAH (2003) emphasises the fact that cross elasticities vary considerably with context and that general knowledge is difficult to establish. BAH (2003) is the only attempt to structure and provide a broad overview of urban transport cross elasticity evidence.

As a first step towards a better understanding of urban passengers' mode switching behaviour and the way policies directed at one mode of transport affect the demand for another, the work presented in this paper includes, to our knowledge, the largest number of transport cross elasticity evidence ever collected and analysed. In doing so, our paper presents, in section 2, the result of a large survey of literature regarding cross-elasticities of demand in urban transport. We present some key methods typically applied to establish cross-elasticities before we move on to present some overall tendencies of the empirical evidence. Section 3 presents cross-elasticity evidence from a travel mode choice model for short distance trips in the Greater Oslo Area. Finally, in section 4 we summarise the paper and point to key findings, future research priorities and policy recommendations.

2. Methods and evidence in the literature

2.1. Library search and contact network

Our review brings in evidence from a wide range of sources. Our 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 would typically consist of combinations of "cross"/ "elasticity", "transport"/ "travel"/ "demand", "urban"/ "city"/ "metropolitan" and "transit"/ "bus"/ "public transport"/ "passenger", and so on. Additionally, we contacted, directly, a fair number of colleagues across the globe, who we considered likely to either hold unpublished material or to help us point to important pieces of work in this area.

This exercise resulted in some 83 different sources of literature – a number which exceeded our expectations by a good margin. Following a cleaning procedure and priorities, a total of 42 references were included for closer study and were coded into a spreadsheet for the analysis presented in this paper. Of these, 28 were primary sources and 14 secondary (cited) sources. From this sample of 42 references, exactly 500 different cross-elasticity estimates are recorded. Table 1 and figure 1 describe some key characteristics of our sample. The cross elasticity literature is spread over six decades with publications spanning the period 1962 to forthcoming (2017). Data used in these works date from 1961 to 2015. It is evident that European contributions dominate the literature, followed by North American (mainly USA) contributions.

Table 1. Sample literature by year of publication and by date of data

Decade	Number of references	Data years covered*
N/A		5 (typically secondary sources)
1960s	1	3
1970s	7	6
1980s	4	2
1990s	6	9
2000s	10	16
2010s	12	1
Forthcoming	2	
Total	42	42

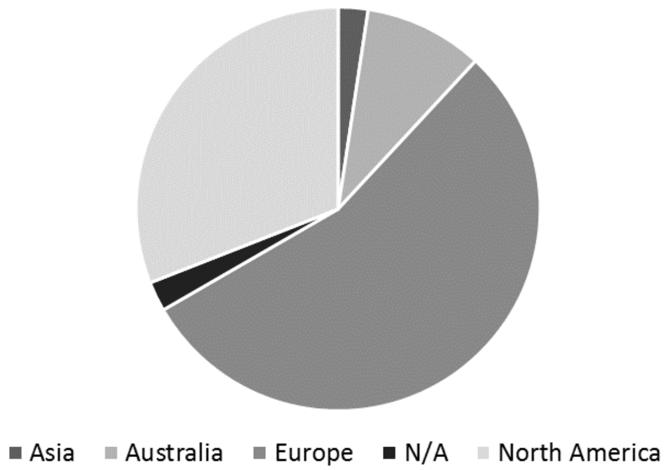

Fig. 1. Reviewed literature by study location, N=42

2.2. Methodologies applied and data types used

The standard textbook calculation of cross-elasticity of demand for mode i with respect to mode j (hereafter denoted ε_{ij}) is the point elasticity, which is established the same as with own-elasticities (ε_{ii}):

$$\varepsilon_{ij}^{\ point} = dQ_i/dP_j * P_j/Q_i \tag{1}$$

where Q_i is demand for mode i and P_j is an attribute of mode j (for example its price). This calculation of point elasticity requires the demand function to be continuous and differentiable.

In practice, demand functions are not always established, or they cannot be differentiated. This would be the case, e.g. when modal substitution is obtained by running transport (or choice) models and comparing modal shares before and after a change to one mode's attribute or, more generally, in cases where there are only two observations of Q_i and P_j before and after a change takes place. The standard approach would either be to establish a linear elasticity (Preston, 1998; Balcombe et al., 2004) or an arc elasticity (Balcombe et al., 2004), defined as:

$$\varepsilon_{ij}^{arc} = \frac{lnQ_{i0} - lnQ_{i1}}{lnP_{j\,0} - lnP_{1j}} \tag{2}$$

$$\varepsilon_{ij}^{line} = \frac{(Q_{i0} - Q_{i1})(P_{j0} + P_{j1})}{(Q_{i0} + Q_{i1})(P_{j0} - P_{j1})} \tag{3}$$

where subscripts 0 and 1 refer to *before* and *after* the intervention, respectively.

Following Dodgson (1986) and for modes which are substitutes for each other, cross-elasticities can also be calculated from own-elasticities, relative market shares and diversion factors, where the latter is a relative measure of the demand change in i compared to the demand change of j.

$$\varepsilon_{ij}^{deduced} = \left|\varepsilon_{jj}\right| \frac{Q_j}{Q_i} \delta_{ji} \tag{4}$$

where ε_{jj} is mode j's own-elasticity and Q_j/Q_i is the two modes relative market shares. The diversion factor, δ_{ji}, is a measurement of how many of those who leave mode j when P_j rises that transfer to mode i. The diversion factor is given as $\frac{(Q_{i1} - Q_{i0})}{(Q_{j1} - Q_{j0})}$. When the own-elasticity is given as a linear elasticity ($\frac{(Q_{j0} - Q_{j1})(P_{j0} + P_{j1})}{(Q_{j0} + Q_{j1})(P_{j0} - P_{j1})}$) it is easy to see that equation (4) reduces to equation (3). However, equation (4) constitutes the basis for a 3rd method to establish cross-elasticities, that is by deducing it from known/assumed measures. For instance, when market shares and own-elasticities are known, one might assume a reasonable diversion factor (e.g. by a literature review) and calculate the corresponding cross-elasticity on that basis.

It follows from this that the relative market share Q_j/Q_i plays an important role in determining the size of the cross elasticity estimate. In an extreme example where mode i has 99 % market share and mode j only 1% market share, it is obvious that even a small change in Q_i which diverts to mode j will cause a proportionately large change in Q_j. A mode shift in the opposite direction, from j to i will, in this example, only cause a negligible change in Q_i. Given the fact that modal split differs substantially between settings, it follows that cross-elasticities of demand are highly context-specific and not readily transferable. Diversion factors will also differ but compared to the highly context specific relative market shares they are, as BAH (2003) puts it, "relatively stable and more readily transferable" (p. 20).

Figure 2 illustrates how the use of these three main approaches to establishing cross-elasticities is spread among our sample, both as a proportion of all elasticity estimates recorded and as a proportion of individual references. From the figure, we see that arc/line elasticities are less often used as main approach (right figure), but that this method typically produces a relatively large number of cross-elasticity estimates once it is used. This is because arc-elasticities are often calculated by transport models, where you can perform a sequence of different policy simulations (varying altered attribute and size of change) with relative ease. The many observations labelled 'not clear' consist for a large part of secondary, cited sources.

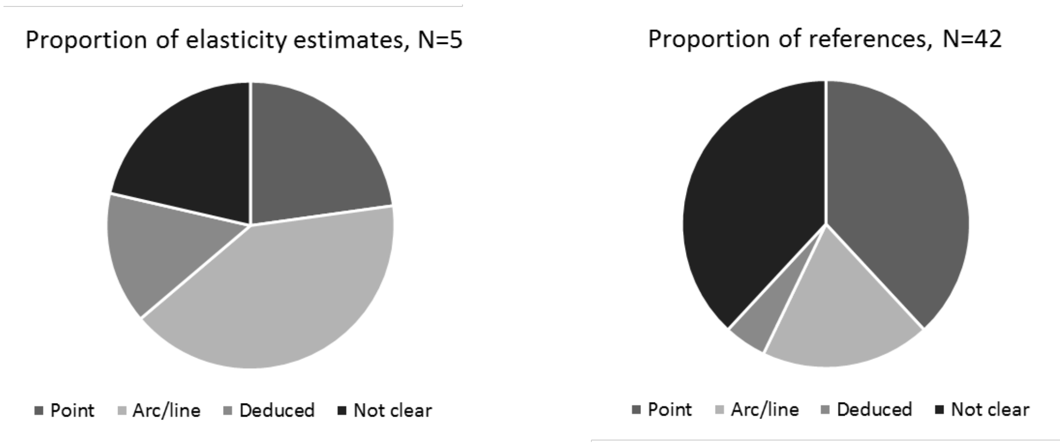

Fig. 2. Prevalence of three different ways to establish cross-elasticities in our sample. Proportion of estimates and proportion of references.

Cross elasticities of demand are estimated on quite different data. Figure 3 illustrates this. Cross-sectional, time-series and panel data are all well represented in the literature. It is worth noting that one reference relies solely on stated preference data. While the common wisdom is that SP data is not suited for forecasting purposes, Taplin et al. (1999) argue that SP can be used for short run commuter elasticities because their demand is constant in the short run and tied up in time and space. On this basis, they present short run cross-elasticity estimates for commuter travel.

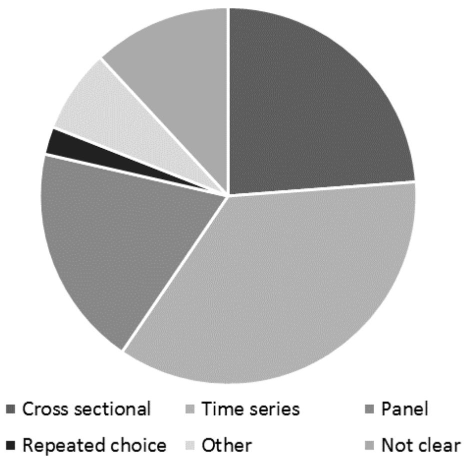

Fig. 3. Type of data used to establish cross-elasticities of demand. N=42

As it is not possible to measure/observe cross-elasticity by cross sectional data alone, this type of data has to be applied by some form of modelling (e.g. estimating a model on cross sectional data and simulating/calculating different demand effects by this model).

2.3. Cross-elasticity evidence

The 500 reported cross elasticities of demand have been coded according to numerous factors. Most importantly, of course, are: mode i; mode j; attribute P; and estimated cross elasticity ε_{ij}.

In this way, each estimate is defined as "elasticity of demand for mode j with respect to attribute P of mode i", for example elasticity of demand for car with respect to bus fare. On one occasion, cross elasticities were presented as ranges rather than exact estimates. For the purpose of this analysis, we recorded midpoint values.

There are numerous such cross-elasticity relations between different modes (car, bus, tram, walk, etc.) and for different attributes (IVT, price, headway, etc.). Table 2 presents the overall findings in terms of mean (average) reported of key relations. The table shows that the average cross elasticity of demand for car travel with respect to public transport fares is 0.055 based on 44 reported estimates, suggesting that a 1% public transport fare reduction on average reduces car use by 0.055 percent. It is evident that car attributes affect public transport demand a lot more than public transport affects car demand. For example, a 1% increase in car costs increases public transport demand on average by 0.248%. Among the car attributes, both the demand for public transport and for walk/cycling are most sensitive to car travel time.

Table 2: Overall average values of key cross elasticity relations.

Demand for	Car			PT			Walk/ cycle			
With respect to	PT fares	PT service	PT time (IVT, access & egress)	Car petrol price	Car any cost (parking, fuel, toll)	Car travel time	Car any cost (parking, fuel, toll)	Car travel time	PT fares	PT time (IVT, wait, access, egress)
Mean ε_{ij} (N)	0.055 (44)	0.008 (8)	0.057 (18)	0.246 (188)	0.248 (217)	0.818 (41)	0.105 (9)	0.571 (8)	0.053 (13)	0.035 (26)

Reviews of own-demand elasticities suggest that they vary systematically with estimation method, model specification, data source and so on (Wardman, 2012; Wardman, 2014; Nijkamp and Pepping, 2003; Holmgren, 2007). The total averages in table 2 should therefore be broken down by several contextual and methodological factors.

In the following, blank cells indicate that only two or fewer cross-elasticity estimates have been recorded. They are not included, since an average value is regarded as not meaningful.

Table 3 presents average values of cross-elasticities and how they vary with time horizon, trip purpose, and location. A few observations are worth noting. One is that, in particular in the cases of demand for public transport with respect to car attributes, long run cross-elasticities are not consistently larger than short run elasticities. This mixed evidence of long run vs. short run cross-elasticities is indeed also observed by BAH (2003), who suggest that long run cross-elasticities may well be lower because of more scope for adaptive behaviours.

The conventional wisdom that business and commuting trips are less elastic appears to only apply to own-elasticities. Our evidence suggests the opposite goes for cross-elasticities. In particular, when it comes to demand elasticity of public transport with respect to car attributes, business and commute trips stand out as the most likely to switch from car to public transport. This combination of relatively small own-elasticities and relatively large cross-elasticities for public transport demand for business and commute trips has implicit impacts on the income elasticity of demand through the property of homogeneity of degree zero of demand in prices. It implies that these trips have a smaller income elasticity of demand, all other things equal.

Table 3: Average cross-elasticity of demand (N in brackets) by factors relating to the trip and time horizon.

Demand for **With respect to**	**Car** **PT fares**	**Car** **PT service**	**Car** **PT time (IVT, access, egress)**	**PT** **Car petrol price**	**PT** **Car any cost (parking, fuel, toll)**	**PT** **Car travel time**
Time horizon:						
Short run	0,041 (6)	0,007 (7)	0,020 (6)	0,207 (87)	0,238 (98)	1,319 (11)
Long run	0,045 (10)		0,096 (9)	0,339 (47)	0,287 (63)	0,740 (25)
Other/unclear	0,062 (28)		0,011 (3)	0,226 (54)	0,222 (56)	0,110 (5)
Trip purpose:						
Commute	0,065 (26)	0,007 (7)	0,04 (4)	0,350 (30)	0,373 (36)	1,060 (11)
Leisure	0,054 (4)		0,076 (4)	0,218 (16)	0,249 (22)	0,805 (11)
All purposes	0,029 (5)		0,02 (6)	0,225 (19)	0,209 (24)	0,097 (3)
Business	0,029 (4)		0,109 (4)	0,558 (14)	0,490 (20)	1,239 (10)
Education				0,015 (6)	0,015 (12)	0,060 (6)
Non-commuting				0,427 (22)	0,427 (22)	
Other/unclear	0,053 (5)			0,131 (81)	0,131 (81)	
Location:						
Urban	0,057 (27)	0,007 (7)	0,02 (6)	0,176 (98)	0,174 (103)	0,097 (3)
Inter-urban	0,04 (3)			0,456 (21)	0,456 (21)	
Long distance	0,042 (7)		0,096 (7)	0,115 (9)	0,115 (9)	0,545 (9)
All				0,187 (6)	0,187 (6)	
Inter-urban to/from metropolis				0,520 (8)	0,520 (8)	
Suburban metropolis				0,298 (18)	0,298 (18)	
Regional	0,033 (4)		0,053 (3)	0,131 (4)	0,131 (4)	0,920 (3)
Other/unclear				0,298 (24)	0,294 (48)	1,044 (24)

In table 4, cross elasticities of demand are presented according to characteristics of the studies: year of publication, type of data, and so on. Earlier studies (before year 2000) report on average consistently higher cross-elasticity estimates than more recent studies. Cross sectional data and choice data tend to produce lower cross-elasticities than do time series and panel data. The tendency is for disaggregate data to produce less elastic cross-modal demand. Obviously, these aspects are related. The type of data, their aggregation and type of elasticity are mutually connected.

Table 4: Average cross-elasticity (N in brackets) by factors relating to the study.

Demand for	**Car**	**Car**	**Car**	**PT**	**PT**	**PT**
With respect to	**PT fares**	**PT service**	**PT time (IVT, access, egress)**	**Car petrol price**	**Car any cost (parking, fuel, toll)**	**Car travel time**
Publication year						
Before 2000	0,067 (28)	0,007 (7)	0,057 (18)	0,282 (35)	0,285 (59)	1,044 (24)
Year 2000 and later	0,036 (16)			0,237 (153)	0,234 (158)	0,499 (17)
Type of data						
Cross sectional data	0,07 (15)		0,026 (12)	0,092 (11)	0,107 (14)	0,327 (11)
Time series data				0,228 (67)	0,225 (69)	
Panel data (classic)				0,282 (74)	0,282 (74)	
Repeated choices	0,055 (3)			0,173 (3)	0,173 (3)	
Other/Unclear	0,046 (24)	0,007 (7)	0,118 (6)	0,258 (33)	0,272 (57)	0,998 (30)
Aggregation						
Disaggregate	0,032 (13)		0,026 (12)	0,095 (12)	0,109 (15)	0,327 (11)
Aggregate	0,008 (7)	0,007 (7)		0,254 (142)	0,252 (144)	
Other/Unclear	0,082 (24)		0,118 (6)	0,263 (34)	0,274 (58)	0,998 (30)
RP/SP						
RP	0,079 (16)		0,031 (9)	0,252 (147)	0,248 (152)	0,508 (6)
SP	0,055 (3)			0,173 (3)	0,173 (3)	
Combined	0,014 (3)		0,011 (3)	0,019 (5)	0,019 (5)	0,110 (5)
Other/unclear	0,044 (22)	0,007 (7)	0,118 (6)	0,258 (33)	0,272 (57)	0,998 (30)
Type elasticity						
Point	0,055 (3)			0,329 (102)	0,329 (102)	
Arc	0,025 (15)		0,026 (12)	0,076 (53)	0,082 (58)	0,327 (11)
Deduced	0,029 (13)	0,007 (7)	0,118 (6)	0,208 (6)	0,208 (6)	0,815 (6)
Other/unclear	0,091 (18)			0,270 (27)	0,279 (51)	1,044 (24)

Despite a relatively large N of 500 observations, the data does not allow for many cross-tabulations. Table 5 is an exception and shows cross-elasticities of demand for public transport with respect to car "any cost" (parking, fuel and toll). It crosstabs trip purpose by time horizon and by elasticity type. Again, we observe that long run estimates are almost consistently lower than short run estimates, and that point elasticity estimates are consistently larger than Arc/line elasticities. The latter is likely to result from the underlying approach. Point elasticities are typically calculated from time series data, whereas arc elasticities are typically used when the evidence comes from model runs and choice models.

Table 5: Crosstab of cross-elasticity of demand for public transport with respect to car 'any cost'. Trip purpose by time horizon and by elasticity type. (N in brackets)

	Short run	**Long+medium run**	**Point**	**Arc**
Commute	0,454 (13)	0,327 (23)	0,423 (18)	0,068 (3)
Leisure	0,455 (6)	0,175 (16)	0,236 (5)	0,073 (3)
All purposes	0,210 (16)	0,178 (6)	0,235 (18)	0,130 (6)
Business	0,810 (6)	0,380 (13)	0,940 (4)	-
Education	0,018 (4)	0,014 (8)	-	-
Non-commuting	0,366 (8)	0,521 (8)	0,427 (22)	-

3. Model evidences for the Oslo Area

In this part of the paper we present analyses on cross-modal substitution conducted on the basis of a recently established travel mode choice model for short distance trips in the Greater Oslo Area (hereafter referred to as MPM23). The purpose is to show how cross-elasticities vary with submarkets and why.

The model development is documented in details in the Norwegian report by Flügel et al (2015) and is also presented in a scientific working paper (Flügel et al 2016). Here, we only briefly explain the modelling and simulation approach (section 3.1.) before we present and discuss results on cross-elasticities (3.2).

3.1. Methodology

Travel mode choice model MPM23

MPM23 is an empirical model based on 14947 travel observations stemming from the telephone survey in Ruter MIS. Ruter MIS has been conducted continuously since 2006 with about 6000 interviews a year. It is administrated by Ruter AS, the public transport managing company of Greater Oslo. Respondents report a trip diary with specific information, like transport mode used, trip purpose etc., regarding all trips made the day before the interview is conducted. Since 2014, also location of origin and destination is reported; that enables the coding of Level-of-Service (LOS; e.g., travel time, cost, number of interchanges, etc.) data of all transport modes from network models, which is crucial information for the building of travel mode choice models.

MPM23 is set up as a nested logit model (Williams 1977, Daly and Zachary 1978). Individual choice sets are defined prior to estimation, consisting of a maximum of 9 travel alternatives, but defining "unavailable" travel modes using information about geographical relation and the traveler (e.g. the alternative "car driver" is defined as available only for people with a driver's license). Figure 4 shows the alternative and how they are structured in the model.

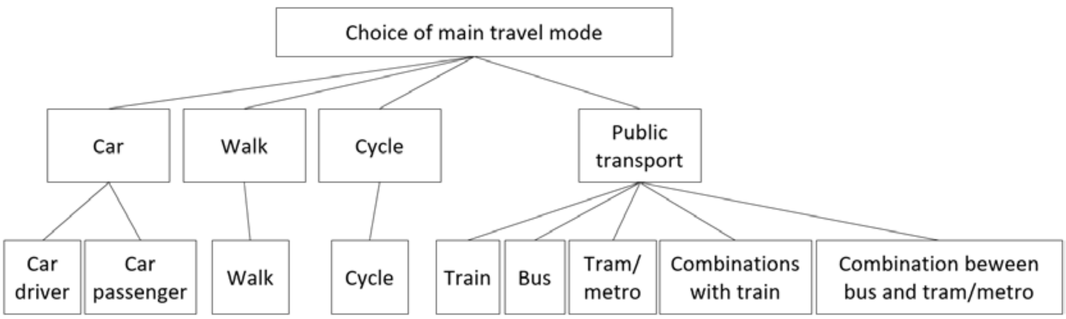

Fig. 4: Structure of nested logit model for MPM23

In the analysis in this paper, we combine the alternative within the nests and only investigate demand effects across the nests car, walk, cycle and public transport (PT).

The 120 parameters underlying MPM23 are empirically estimated using maximum likelihood methods. After some testing it was found a specification where all parameters had expected sign and reasonable size. The Value of Time (VoT) in different transport modes was, however, somewhat lower than expected but within a plausible range.

Policy simulation

MPM23 is implemented as a policy simulation tool in standard Microsoft-Excel spreadsheets. The method of sample enumeration (Ben-Akiva and Atherton 1977) is applied and calculated average choice probabilities (for the whole area or different submarkets) are interpreted as market shares. This allows very fast scenario simulations (the computation time is around 2 seconds).

Scenarios are defined as changes in one or several LOS variables as %-points of the original LOS values derived from the network models and travel survey. For instance, a 1% decrease for the ticket prices for PT is specified as shown in Figure 5.

MPM23 Version 1.1, Institute of Transport Economics

Geographic area of policy measure

Entire Greater Oslo

		Reference	Measure
Level of Service (LoS)		*% of orgininal value*	
Car	**Travel time**	100,00 %	100,00 %
	Travel cost (fuel&toll)	100,00 %	100,00 %
Train	**Access/egress time**	100,00 %	100,00 %
	Wait time	100,00 %	100,00 %
	Single ticket price	100,00 %	99,00 %
	No. of interchanges	100,00 %	100,00 %
	In-vehicle time	100,00 %	100,00 %
Bus	**Access/egress time**	100,00 %	100,00 %
	Wait time	100,00 %	100,00 %
	Single ticket price	100,00 %	99,00 %
	No. of interchanges	100,00 %	100,00 %
	In-vehicle time	100,00 %	100,00 %
Metro/LRT	**Access/egress time**	100,00 %	100,00 %
	Wait time	100,00 %	100,00 %
	Single ticket price	100,00 %	99,00 %
	No. of interchanges	100,00 %	100,00 %
	In-vehicle time	100,00 %	100,00 %

Fig. 5: Extract of the policy definition spreadsheet in MPM23, simulation of a 1% decrease in PT prices

The spreadsheet calculates effects on travel mode choice in different submarkets (geographical relation, trip purpose, trip distance groups); changes in market shares, (cross)elasticities and diversion factors are calculated automatically.

Regarding the interpretation of the size of elasticities, it has to be stressed that MPM23 does not calculate newly generated transport (just mode choice). Hence, the elasticities found by the model may be a bit smaller in (absolute) size compared to models that model trip generation or trip frequency.

3.2. PT price cross-elasticities by different submarkets

We start with analyzing effects of a price reduction for all types of PT by 1 percent (as illustrated in Figure 5). For the interpretation, it may be of importance that price regards only single tickets (travelers with period tickets get assigned no costs in the choice model).

Before presenting cross-elasticities, it is interesting to look at some mathematical “drivers” for cross-elasticities (see equation 4, $\varepsilon^{deduced}$, in section 2.2): own elasticities and diversion factors. Note that diversion factors sum always up to 100% as we only model travel mode choice and not generated or suppressed travel.

Figure 6 shows own elasticities (absolute value) and diversion factors for all trips in Greater Oslo Area and for different submarkets defined by trip purpose or trip distance groups.

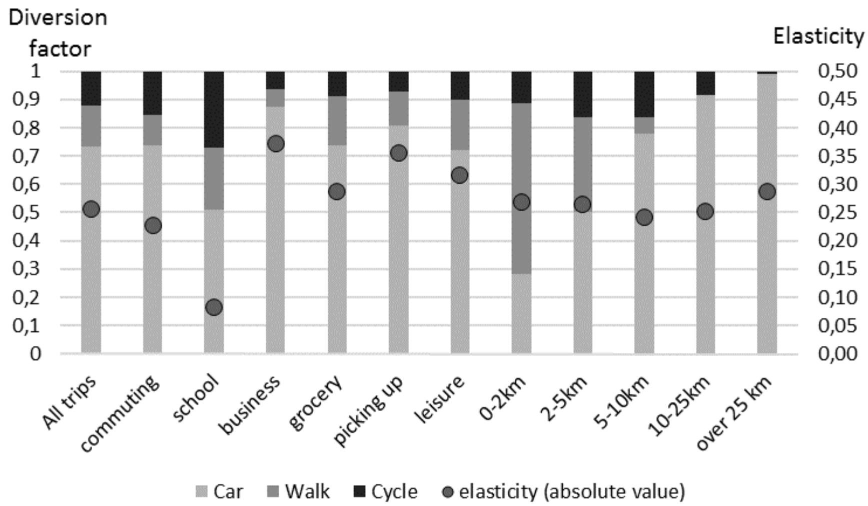

Fig. 6: Price elasticity (1% arc) and diversion factors when reducing PT ticket prices, simulated with MPM23

Considering all trips, the (own) price elasticity of PT is simulated at -0.256 (shown as 0.256 on the right axis in figure 6). This corresponds well with other values found in the literature (see Balcombe et al., 2004). The price sensitivity is lowest for school trips (because most pupils use period tickets) and highest for business trips. Own price elasticity is rather constant with trip distance. Looking at the diversion factors (left axis of figure 6) one sees that car is the main substitution mode for PT, except for very short trips. For all trips, the 0.256 percent increase in PT trips results from: 74% previous car trips, 14% previous walk trips, and 12 % previous cycling trips. The diversion factors for walk decrease – not surprisingly – rapidly with trip distance. Diversion factors for cycle first increase and then decrease with distance.

Figure 7, 8 and 9 show market shares and the elasticity of demand for respectively car, walk, and cycle with respect to price changes in PT.

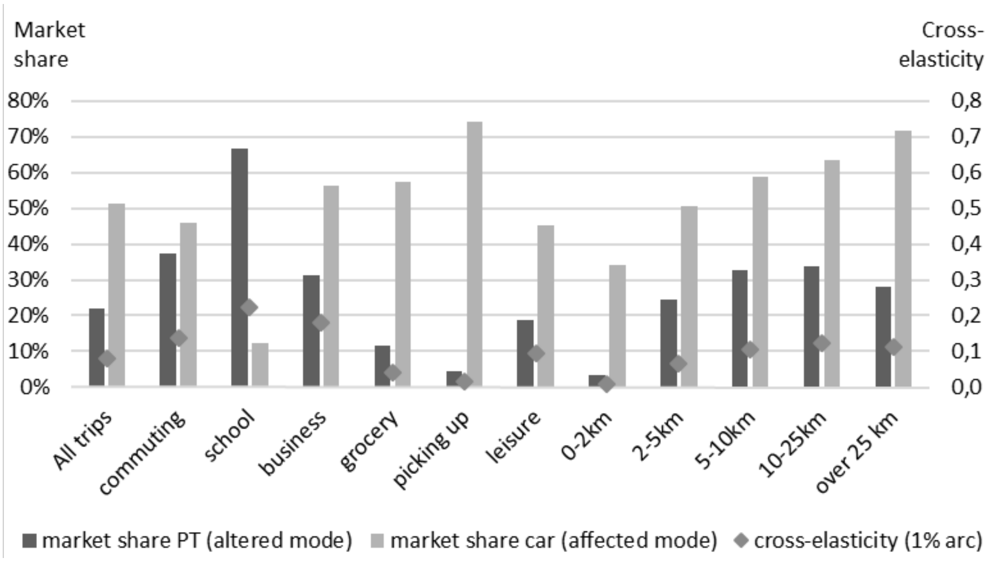

Fig. 7: Markets shares and demand effect of car with respect to PT price reductions, simulated with MPM23

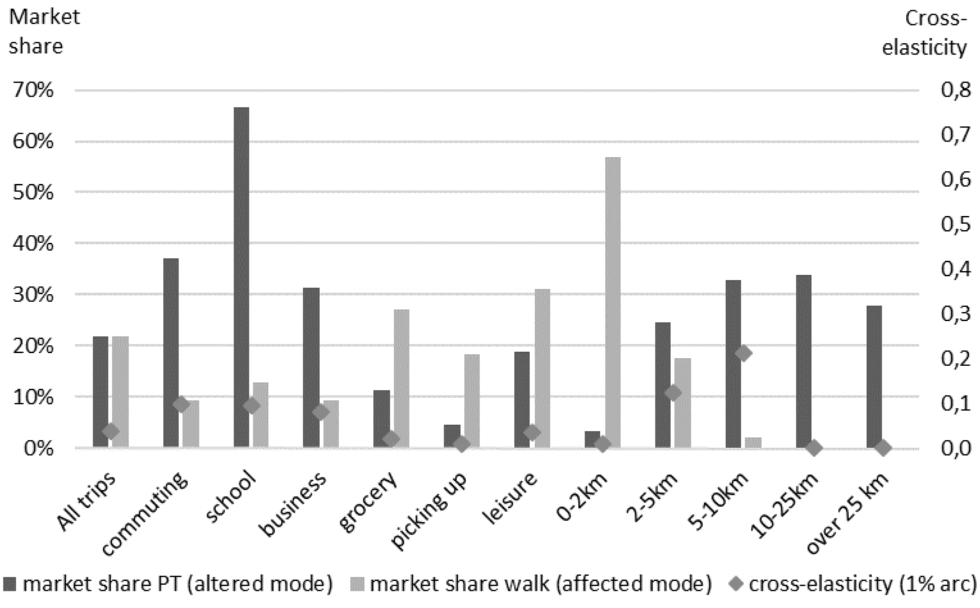

Fig. 8: Markets shares and demand effect of walk with respect to PT price reductions, simulated with MPM23

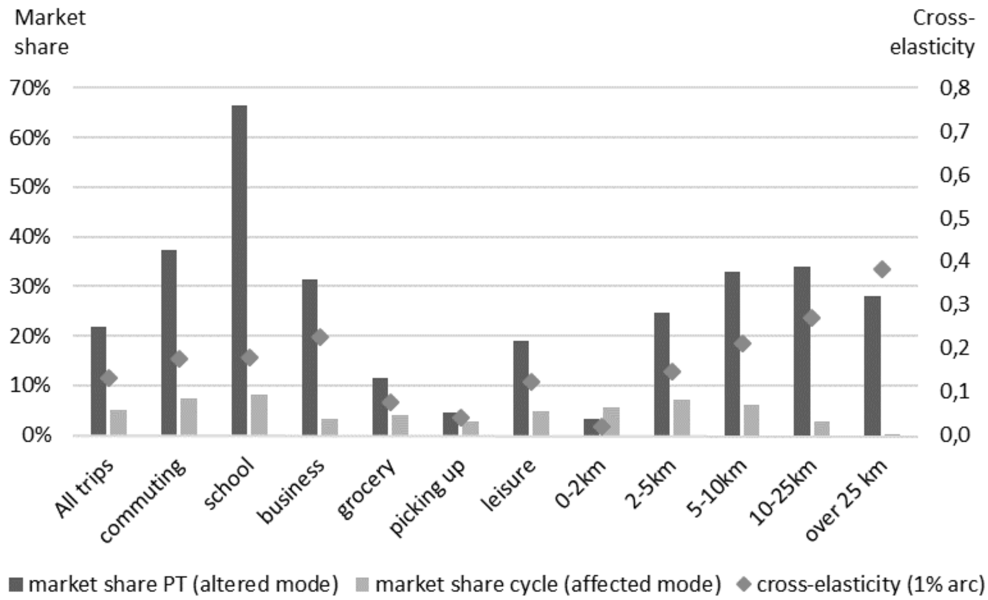

Fig. 9: Markets shares and demand effect of cycle with respect to PT price reductions, simulated with MPM23

Considering all trips (the left most panel in figures 7-9), the simulated 1% arc cross-elasticities on car, walk and cycle are 0.08, 0.04 and 0.14 respectively. Note that this does not follow the order of diversion factors (Figure 6). In particular, the relative demand effect of cycle is greatest, not as a consequence of a high diversion factor but presumably because of a low market share for cycle in Oslo Area (around 5%).

Indeed, when looking at the variation across submarkets it is evident that cross-elasticities depend a lot on the underlying market shares. This does not come as a surprise, as relative market shares are – besides own elasticities and diversion factors – the 3rd mathematical driver behind cross-elasticities (see equation 4, $\varepsilon^{deduced}$, in section 2.2). From Figure 8 and 9 we see that cross-elasticities actually increase with trip distance (as long as walk is defined as availably). From purely looking at diversion factors the opposite could be expected, but the relative market share of PT increases with trip distance and this fact has a large influence on the size of the cross-elasticities.

The relation between relative market shares and cross-elasticities is illustrated in Figure 10. Here, relative market share is computed as [market share of PT] divided by [market share of alternative mode]. A relative market share of 4 would then mean that PT's market share is four times greater than the alternative mode.

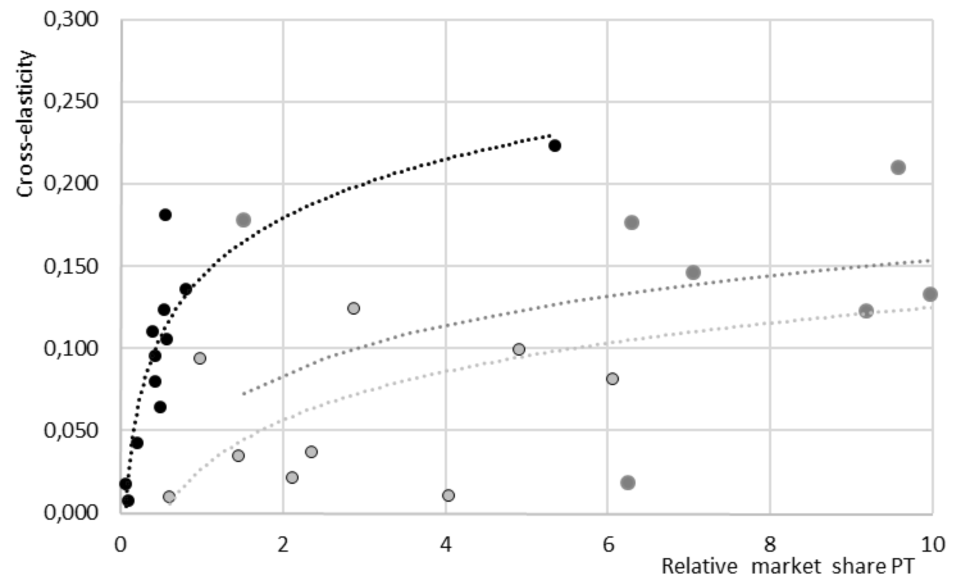

Fig. 10: Relative market shares of PT and price cross-elasticity (1% arc), simulated for various sub-markets with MPM23. Zoomed. Black dots are car; pale dots with black border are walk; grey dots are cycle.

Interestingly, the correlation between cross-elasticity and relative market share appears stronger than the correlation between cross-elasticities and diversion factors. The somewhat unexpected increase in cross-elasticities with trip distance for walk and cycle leads actually to a negative correlation in the here analyzed submarkets as illustrated in Figure 11.

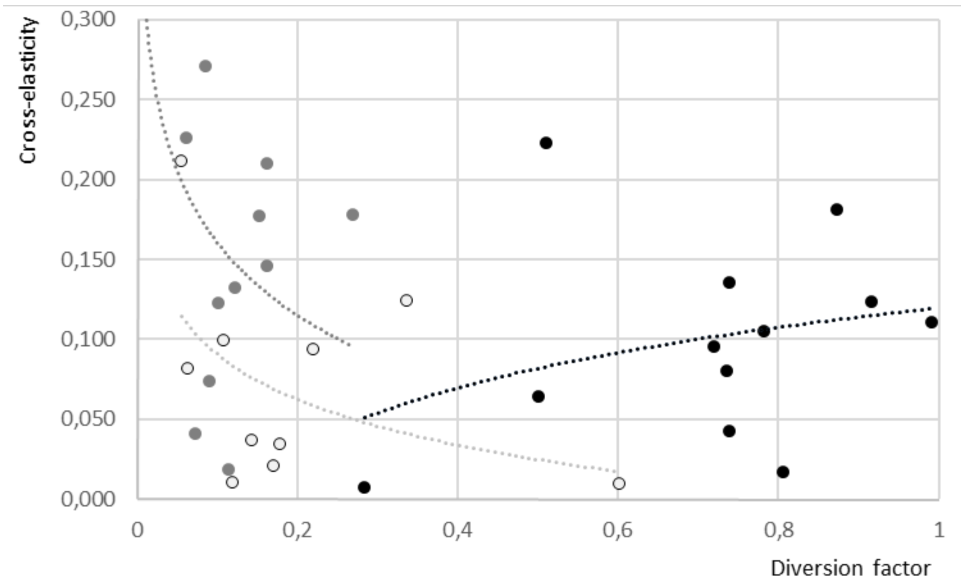

Fig. 11: Diversion factors and PT price cross-elasticity (1% arc), simulated for various sub-markets with MPM23. Black dots are car; pale dots with black border are walk; grey dots are cycle.

3.3. Car price cross-elasticities by different submarket

Next we look at effects of reductions in car prices on demand for other transport modes (Figure 12). The price for cars in MPM23 is defined as out-of-pocket-cost including only fuel and road tolls.

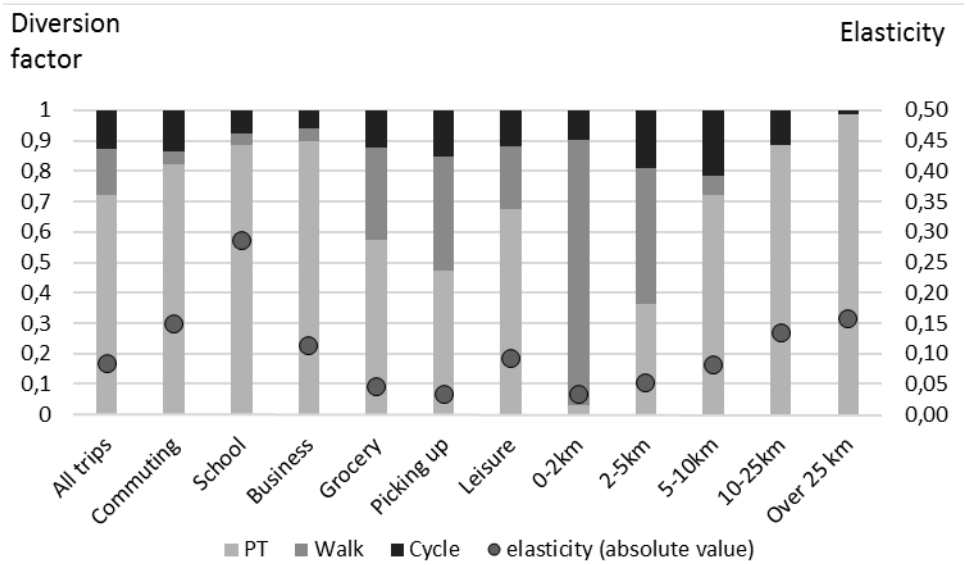

Fig. 12: Car price elasticity (1% arc) and diversion factors when reducing car prices, simulated with MPM23

The car price elasticity for all trips is simulated at 0.084 and varies between 0.03 and 0.29 in the analyzed submarkets. Opposed to the PT price elasticity the relative demand effect for car is highest for school trips. This may again be related to the underlying markets shares illustrating that markets shares also play a role for price elasticities (not only price cross-elasticities). The pattern of diversion factors is corresponding to the ones in Figure 6.

Figures 13-15 show demand effects for respectively PT, walk and cycle given a 1% reduction in out-of-pocket-cost for car.

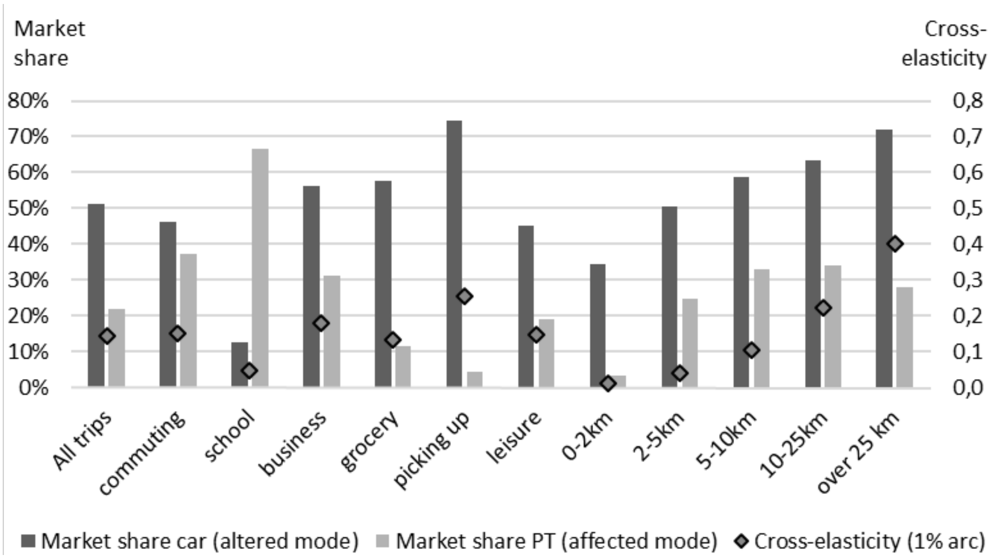

Fig. 13: Market shares and demand effect of PT with respect to car price reductions, simulated with MPM23

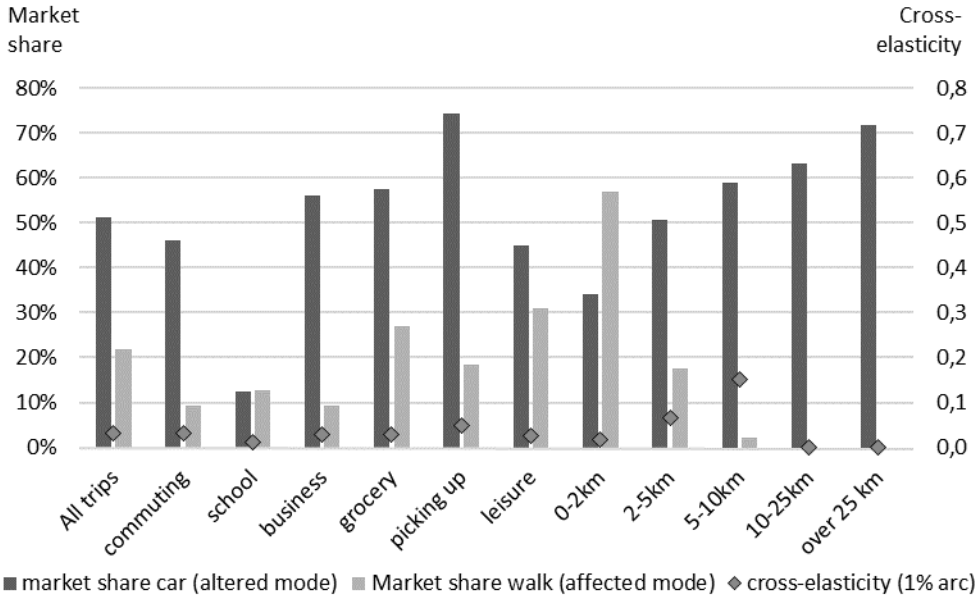

Fig. 14: Markets shares and demand effect of walk with respect to car price reductions, simulated with MPM23

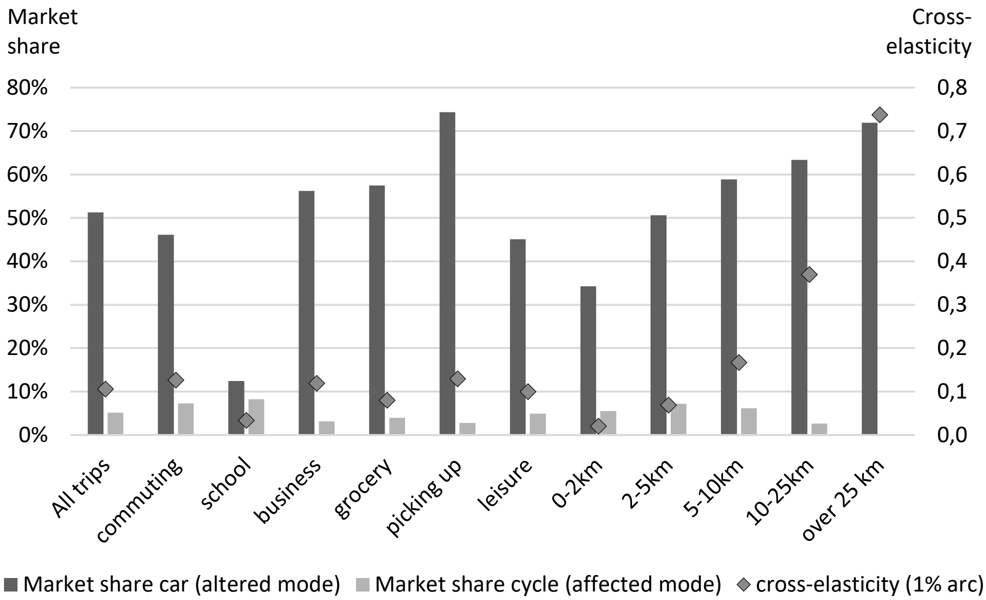

Fig. 15: Markets shares and demand effect of cycle with respect to car price reductions, simulated with MPM23

For walk and cycle (figure 14 and 15) the pattern of cross-elasticities across submarkets when altering car is somewhat similar to effects seen when alternating PT (figures 8 and 9).

Comparing the pattern in cross-elasticities across submarkets in Figure 13 and 7, we see that the effects for car and PT are not very symmetrical. This is again a consequence of the (relative) market shares in submarkets as the absolute demand effects appear somewhat more symmetric than the relative demand effects (i.e. cross-elasticities). This is shown in Table 6.

Table 6: Absolute and relative change of 1% price reduction in the Greater Oslo Area.

Changes in daily trips after 1% price reduction		Absolute change		Relative change	
		Affected mode			
Submarket	Altered mode	PT	Car	PT	Car
All trips	PT	2144	-1576	0.26 %	-0.08 %
	Car	-1197	1660	-0.14 %	0.08 %
Commuting	PT	896	-662	0.23 %	-0.14 %
	Car	-594	723	-0.15 %	0.15 %
School trips	PT	49	-25	0.08 %	-0.22 %
	Car	-29	32	-0.05 %	0.29 %
Business trips	PT	94	-82	0.37 %	-0.18 %
	Car	-45	51	-0.18 %	0.11 %
Grocery	PT	331	-244	0.29 %	-0.04 %
	Car	-152	266	-0.13 %	0.05 %
Picking up	PT	67	-54	0.36 %	-0.02 %
	Car	-47	100	-0.25 %	0.03 %
Leisure	PT	707	-509	0.32 %	-0.10 %
	Car	-330	487	-0.15 %	0.09 %
0-2km	PT	100	-28	0.27 %	-0.01 %
	Car	-4	132	-0.01 %	0.03 %
2-5km	PT	631	-316	0.26 %	-0.06 %
	Car	-92	255	-0.04 %	0.05 %
5-10km	PT	602	-470	0.24 %	-0.11 %
	Car	-262	364	-0.11 %	0.08 %
10-25km	PT	574	-525	0.25 %	-0.12 %
	Car	-507	573	-0.22 %	0.13 %
Over 25 km	PT	238	-236	0.29 %	-0.11 %
	Car	-332	336	-0.40 %	0.16 %

4. Summary, conclusions and policy recommendations

This paper has presented the largest collection of transport demand cross-elasticity evidence ever assembled. While urban transport demand has been the main focus, evidence of regional transport is also included. Evidence of cross-modal demand interactions in Greater Oslo is also presented.

We have shown that for some journey purposes, relatively large cross-elasticities can co-exist with relatively small own elasticities (and vice versa), so cross-mode substitutability cannot be inferred simply from own elasticities. Also, cross-elasticities alone may give misleading impressions of the pattern of cross-modal substitution. Further work is needed on the magnitude and direction of changes in attributes of modes and their relationship with own- and cross-elasticities.

The general tendency of the collected evidence is for public transport to have less impact on demand for car and walk/cycling than car policies have on the demand for walk, cycle and public transport. This asymmetry stands out very clearly from table 2, which suggests that the impact of car travel time on public transport is, on average, 14 times larger than the reverse impact of public transport travel time on car. A similar magnitude of difference appears when comparing the impact of car versus public transport on walking and cycling.

Policy makers should therefore understand that 'carrot' measures of improving public transport or improve walkability with the goal of reducing car use, are likely to be exceedingly optimistic.

A main reason for this asymmetry relates to the different modes' market shares. Where car is the dominant transport mode – which it often is – a percentage change in demand for car which diverts to/from other modes will manifest as large relatively change in demand for alternative modes. The analyses in section 3 gave some empirical illustration for the fact that (relative) market shares are essential for the interpretation of cross-elasticities. Indeed, it was shown that the variation in simulated cross-elasticities across submarkets may not follow intuition before considering the underlying market shares (e.g. relative demand effect for walk [in respect to car or PT price reduction] increased with distance as a consequence of the rapidly decreasing market share of walk). The simulated diversion factors, on the other hand, were more intuitive (corresponding diversion factors decreased with distance), an observation which supports the claim made in the literature that diversion factors are more stable than cross-elasticities - and thus easier to transfer from one study to the other.

Equation (4) in section 2.2 shows how cross-elasticities of demand rely on own-elasticity, relative market share and the diversion factor. It means that, in addition to relative market shares, the diversion factor, too, plays a crucial role. While the literature suggests that diversion factors are more stable across contexts, diversion factors are still likely to vary substantially. For example, diversion from car to public transport can only occur where public transport exists and is a meaningful alternative.

Due to the strong dependence on market shares and diversion factors, cross-elasticities of demand are indeed highly context-dependent – and much more so than demand own-elasticities. However, despite this importance, market shares and diversion factors are rarely reported in the empirical literature. This is illustrated in figure 16. Market shares were available for coding in less than one-third of our sources, and diversion factors were only presented in five percent of them. The strong message to the research community is, therefore, to always include local information about these crucial aspects when reporting demand cross-elasticities. Without this information, the evidence is inadequate and cannot easily be generalised or transferred to other contexts.

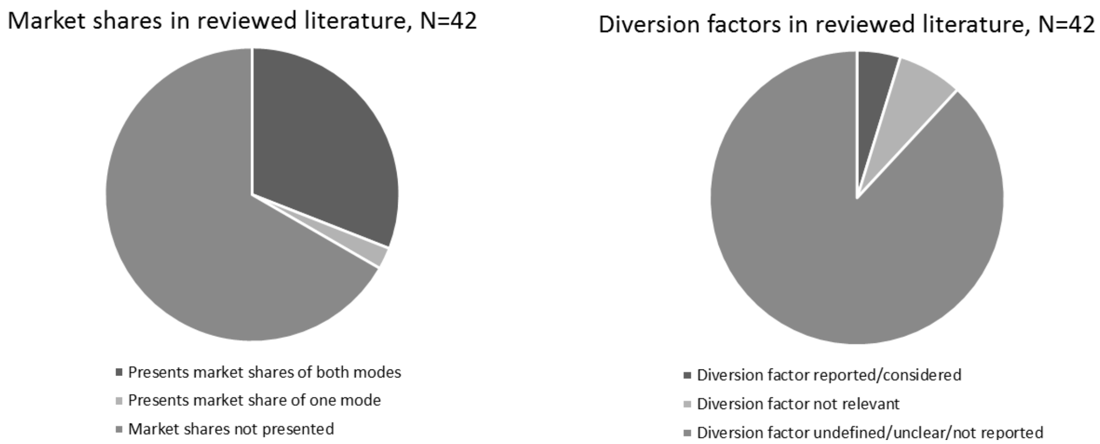

Fig. 16: Despite their importance for cross-elasticities, neither market shares (left) nor diversion factors (right) are commonly reported in cross-modal studies.

More generally, studies that report cross-elasticities of demand should be careful to document market shares, diversion factors, trip purpose, number of available transport modes, and trip lengths. In this way, it will be easier to understand the information in its context and thus develop broader, transferable understanding of interaction between modes.

Diversion factors are in general poorly understood and under-researched. In order to better understand mode switching behaviour, and in order to design effective policies, it advisable to focus efforts on methods to elicit diversion factors and on empirical work that leads to deeper understanding of how various factors affect mode substitution.

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