REVIEW AND META-ANALYSIS OF INTER-MODAL CROSS-ELASTICITY EVIDENCE

Mark Wardman, Jeremy Toner, Nils Fearnley, Stefan Flügel and Marit Killi

1. INTRODUCTION

This paper is concerned with cross-elasticities between modes, and primarily takes the form of a meta-analysis to explore the relationships between cross-elasticities and factors that are expected to influence them. Whilst there are many notable reviews and indeed meta-analyses covering own-elasticities of demand (Webster and Bly, 1980; Goodwin, 1992; Oum et al., 1992; Goodwin et al., 2004; Graham and Glaister, 2004; TRB, 2004; Transport Research Laboratory et al., 2004; Jevons et al., 2005; Hensher, 2008; Litman, 2010; Wardman, 2012, 2014; Wardman and Batley, 2014), in contrast cross elasticities have received far less attention despite being increasingly important to transport practitioners and policy makers.

Reviews of cross-elasticities are contained in Wardman (1997a, 1997b), Goodwin (1992), de Jong and Gunn (2001), Transport Research Laboratory et al. (2004) and Wallis (2004). These are all dated and tend to cover relatively few observations and a limited set of cross-elasticity types. More recent reviews are provided by Fearnley et al. (2017, 2018), covering a larger number of studies and a broader range of cross-elasticity terms. We here build upon the latter reviews with considerably more data and greater detail surrounding variables and modes to report the most extensive review of inter-modal cross-elasticities yet undertaken. Whilst Fearnley et al. (2018) is novel in reporting a meta-regression model on cross-elasticity evidence[1], it is restricted to public transport modes and a far smaller data set than here, and the meta-analysis reported in this paper provides insights from a far larger range of explanatory variables and is the first ever that covers all modes and all attributes.

The main aims of conducting this meta-analysis were:

- to provide an extensive review and synthesis of cross-elasticity evidence given that there are few previous studies and those that have been conducted are limited in scope, coverage and detail;
- to identify and quantify variables related to study context and methodology that drive variations in cross-elasticities;
- to provide a model that can be used both to benchmark emerging and existing evidence and to forecast cross-elasticities for a wide variety of contexts where no other evidence exists.

[1] Holmgren (2007) contains a meta-analysis of cross-elasticities of public transport demand with respect to petrol prices but it contains only 17 observations.

2. DATA ASSEMBLY

2.1 Process and Scope

This review covers a wide range of sources, from scientific publications to unpublished working documents. The initial library search included resources such as ISI, Google Scholar, World Transit Research database, Bureau of Infrastructure, Transport and Regional Economics (BITRE) Elasticities Database Online, Springer Link, Science Direct, and Tylor and Francis Online. Additionally, transport practitioners were contacted who it was felt might be aware of work in the area. The identified references were also scanned in search of further sources of evidence. Although our focus was initially on local and urban travel (Fearnley et al., 2017), we subsequently extended this to include contributions relating to inter-urban and longer distance trips.

An important process was checking for duplicates, particularly given the increasingly common practice of the same piece of research being published in different formats. A few such instances were discovered. Observations were not included where it was not possible to calculate cross-elasticities based on how the results were presented, such as incomplete information, qualitative attribute changes or the variable covering multiple attributes. Some wrong sign cross-elasticities were retained in the assembled data set, on the grounds that their omission could bias the sample against low cross-elasticities, and we return to this issue below.

2.2 The Explanatory Variables

Given that the purpose of this research was to explore and quantify variations in a range of different inter-modal cross-elasticities across studies, we therefore assembled evidence for each study on the following candidate explanatory variables:

- The mode whose demand is affected and the competing mode which is altered;
- The variable that is altered;
- The method used to estimate the cross-elasticity, distinguishing short and long run effects;
- Journey purpose and journey length;
- Market shares of the affected and altered modes;
- The dissemination channel;
- The number of cross-elasticities per study;
- The demand units in which the cross-elasticity is measured and the level of aggregation;
- Year of data collection and reporting;
- Country Gross Domestic Product at purchasing power parity (PPP) in US dollars.

2.3 Overview of Sources

Tables 1 to 3 provide an overview of the data assembled, based on 1096 cross-elasticity estimates obtained from 93 studies. The scope of this review is international and Table 1 lists the countries from where evidence has been sourced. The UK provides the most studies (34%) and cross-elasticities (44%), as in other international meta-analyses (Wardman et al., 2016), in part because of the UK's commitment to evidence based economic appraisal over many years but also because of some of the authors' familiarity with UK research and particularly its grey literature. The USA and Australia between them provide a further 36% of studies and 22% of cross-elasticities. In terms of the number of cross-elasticities, Denmark, Europe, Italy, Netherlands and Norway stand out despite having few studies. This is the result of using the outputs of model systems along the lines of the de Jong and Gunn (2001) elasticity review. 71% of the cross-elasticity observations came from published sources and 31% were from peer-reviewed journal articles.

Table 1: Studies and Cross-Elasticity Estimates per Country

Country	Number of studies	Number of elasticities	Country	Number of studies	Number of elasticities
Australia	15	96	Netherlands	3	49
Belgium	1	4	New Zealand	3	11
Canada	2	9	Norway	3	146
Denmark	1	36	South Korea	2	7
Europe*	2	39	Spain	4	5
France	2	6	Sweden	3	12
Germany	2	8	Taiwan	1	8
Italy	1	32	UK	32	477
Japan	1	1	USA	18	148
Malaysia	1	2	TOTAL	97**	1096

Note: * Europe covers trans-national evidence. ** Of the 93 studies, one covered four countries and one covered two countries.

The earliest study in our data set was published in 1962 covering data for our earliest year of 1961. Table 2 lists the number of studies and cross-elasticity estimates in each of four time periods. The studies provide a good spread over a large time period, with a tendency for more cross-elasticities per study in more recent years.

Table 2: Studies and Cross-Elasticity Estimates by Year of Publication

Year	Studies	Cross-Elasticities
- 1990	22	85
1991 – 2000	21	159
2001 – 2010	29	524
2011 -	21	328
Total	**93**	**1096**

Table 3 presents the distribution of cross-elasticity estimates per study. Multiple observations per study can be obtained for a number of reasons, including different modes, attributes, journey purposes, distances and estimation methods, and distinguishing between short run and long run impacts. Having said that, 37% of studies yielded just one or two cross-elasticities. The largest category, of 41% of studies, yields between three and nine cross-elasticities. Dargay et al. (2010) provided the largest number (180) of observations of (deduced) cross-elasticities covering combinations of fare, total car cost and journey time for 12 different modal combinations and a range of journey purpose and distance segmentations.

Table 3: Distribution of Cross-Elasticity Estimates

Cross-elasticities per Study	Studies	Cross-Elasticities
1	16	16
2	18	36
3-9	38	206
10-15	7	85
16-25	3	61
26-50	6	219
51+	5	473
Total	**93**	**1096**

3 DATA CHARACTERISTICS

3.1 Data Inspection and Cleaning

Range and logic checks were conducted on the assembled data as part of an extensive data cleaning process. Where necessary, we returned to the original source documents to clarify coding.

In almost all reviews or meta-analyses, and indeed with quantitative analysis of primary data, judgements have to be made regarding the quality of the data being examined and whether some observations are sufficiently misleading that they should be removed from consideration. Given that this can be controversial, the assumptions and procedures involved must be clearly set out.

The final assembled dataset contained 13 negative cross-elasticities which violate economic theory given that in the choice contexts under consideration the different modes are substitutes. All of these wrong sign cross-elasticities were for fuel price and were near to zero with, where available, low t ratios. We have taken these to represent a zero cross-elasticity in preference to removing them which effectively treats them as 'average'.

At the other extreme, there are cross-elasticities as high as 2.78. There might be concern that very large cross-elasticities in the data set could be misleading, although noting that these might legitimately arise where a mode has a very low market share. After some inspection and testing, the full data set of 1096 was retained for analysis[2].

3.2 Key Features of Assembled Data

The variables that we collected information about are listed in Table 4 for which we provide summary measures. A key purpose of Table 4 is to set out the number of observations in each category and we leave the discussion of cross-elasticities to the insights provided by the meta-analysis.

Fuel cost is the largest attribute category and accounts for just over a third of observations. Very large samples have also been obtained for fare, which form 21% of the total, in-vehicle time (IVT), and overall journey time (JT), with worthwhile numbers for vehicle miles (VM), access and egress time (ACCEGR), wait time, headway and total car cost (TC). INT denotes the need to interchange as opposed to TT which is the transfer time at an interchange and PARKTIME relates to time spent finding a parking space. The remaining category is a remnant of other car costs (RESTCOST) which covers congestion charge (N=2), toll charge (N=2) and parking cost (N=20). Cost related cross-elasticities form 62% of the total.

The modes are car, bus, rail, metro, light rail transit (LRT), air, walk, cycle and a generic public transport (PT) mode. We distinguish between the mode whose demand is affected and the mode whose attribute is altered, so that CAR_BUS indicates a cross-elasticity of demand for car with respect to some change in bus characteristics.

Of the affected modes, the largest is rail (27%), followed by car (23%), bus (18%), PT (16%), air (6%), cycle, LRT and walk (3% each) and metro (1%). The relatively large number of observations covering rail, given it tends to account for modest shares of travel, is due to the availability of ticket sales data

[2] Even removing the 43 cross-elasticities in excess of one made little difference to the results of the estimated meta-models.

to support econometric analysis. Car dominates the altered mode (52%), as might be expected given its strong market position and the generally ready availability of historic fuel price data, followed by rail (18%), bus (17%), PT (7%), air and LRT (3% each) and metro (1%).

In terms of modal combinations, there are 35 in total, but 20 (57%) categories contain fewer than 10 observations. Each of the combinations of the main modes of car, bus, rail and PT are though well represented, accounting for 876 (80%) of the cross-elasticity observations.

With regard to the method used to obtain the cross-elasticity estimate, we distinguish between those deduced using the relationship between cross and own elasticities set out in equation 1 below, four stage transport models, choice models, observed changes in demand and regression analysis. The latter distinguishes between dynamic econometric analysis of time-series demand data that returns explicitly short run (REGRESSION_SR) and long run (REGRESSION_LR) cross-elasticities, static models where no such distinction is made (REGRESSION_ND), and regression analysis of purely cross-sectional demand data (REGRESSION_CROSS) and aggregated Stated Preference (SP) data (REGRESSION_SP)[3]. The cross-elasticities obtained from discrete choice models distinguish between those estimated to Revealed Preference (RP) data alone (CHOICE_RP), SP data alone (CHOICE_SP) and jointly to RP and SP data (CHOICE_RPSP). The observations are spread reasonably well across the four main methods of deduced (23%), time-series based regression (25%), conventional transport models (18%) and discrete choice models (30%).

Taking the regression based results a little further, the periodicity of the demand data upon which the models were estimated can be allowed for. A distinction was made between those based on half annual and primarily annual (LONGER) data and those estimated to quarterly and monthly data and further assigned to long run (REG_LR_LONGER), short run (REG_SR_LONGER) and no distinction (REG_ND_LONGER) cross-elasticities.

Evidence is obtained from a number of sources. Journals provide around a third of all observations with conference papers accounted for 23%. Unpublished papers, either by academics or consultants, provide just under 30% of the total.

The journey purpose categories combine across a number of sub-categories which have too few observations to be retained separately. The commuting category is made up of 171 observations coded as commuting plus 21 education, 6 commuting and education combined and 40 peak. Leisure is composed of 193 coded as leisure, 15 shopping or recreation, 9 holiday, 53 non-commuting, 11 weekday and 31 off-peak. All contains 408 where the cross-elasticity covered all purposes and 14 where it was non-business. There is a reasonable spread across purposes; the all category is largest (39%) followed by leisure (28%), commuting (22%) and business (11%).

No attempt was made to allocate a precise distance to each observation on the grounds that most cover a range and studies do not always indicate the distance to which the cross-elasticities relate.

[3] This is where individual choice data has been aggregated into market shares for analysis purposes.

However, observations can be readily assigned to distance-based categories. Urban and suburban trips make up 39% of the total. We distinguish between inter-urban trips (INTER) and long distance trips (LONG), which respectively form 29% and 7% of the sample. The latter are inter-urban trips but of the sorts of distances where air is relevant. For urban and inter-urban trips, we additionally identified those that were to/from major metropolitan areas (INTER_METRO and SUBURBAN_METRO). Around 20% of the observations cover a range of distances (ALL_LENGTHS).

Cross-elasticities are estimated at different levels of spatial aggregation. The largest category at 40% is the national level, such as cross-elasticities obtained from national model systems or where there is no form of disaggregation. Cross-elasticities for cities and urban areas are the next largest category, forming 33% of the total. The flow category relates to specific movements, such as rail demand between stations, and accounts for 10% of the total whilst the regional level of aggregation forms only 5%. Only small proportions were recorded as relating to international travel or solely to metropolis. The other category covers the 8% of observations where the spatial definition was irrelevant, unclear or covered a combination of categories.

Table 1 listed the number of studies and observations by country. These can be grouped by area of the world. Around three quarters cover Europe, 14% North America, 10% Australia and New Zealand and 2% Asia. The demand responsiveness measure could relate to trips or trip kilometres, with the former accounting for just over two-thirds of the total.

Cross-elasticities are widely regarded to be sensitive to market shares. Indeed, Dodgson (1986) set out the following relationship:

$$\eta_{ij} = -\eta_{jj}\frac{V_j}{V_i}\delta_{ji} \tag{1}$$

where η_{ij} is the cross-elasticity of demand for mode i with respect to some change in mode j, η_{jj} is the relevant own elasticity on mode j, V_j and V_i denote the respective volumes of demand on modes j and i and δ_{ji} is the diversion factor that denotes the proportion of users of mode j who switch to or are attracted from mode i.

Table 4: Summary Measures for Key Explanatory Variables

TRAVEL ATTRIBUTE		JOURNEY PURPOSE	
FUEL	0.26 (0.02) [0.00:2.59] {383}	LEISURE	0.29 (0.02) [0.00:1.80] {312}
VEHICLE MILES (VM)	0.05 (0.12) [0.00:0.24] {23}	COMMUTE	0.22 (0.02) [0.00:2.78] {238}
FARE	0.12 (0.01) [0.00:1.31] {231}	BUSINESS	0.38 (0.05) [0.00:2.59] {124}
IN-VEHICLE TIME (IVT)	0.46 (0.04) [0.00:2.78] {178}	ALL	0.18 (0.01) [0.00:1.74] {422}
ACCESS AND EGRESS (ACCEGR)	0.12 (0.02) [0.00:0.38] {31}	ANALYSIS METHODS	
WAIT TIME	0.10 (0.04) [0.00:1.00] {26}	DEDUCED	0.20 (0.02) [0.00:1.80] {253}
JOURNEY TIME (JT)	0.31 (0.04) [0.00:1.80] {102}	REGRESSION_SP	0.26 (0.07) [0.05:1.10] {16}
TRANSFER TIME (TT)	0.10 (0.02) [0.07:0.16] {5}	REGRESSION_CROSS	0.44 (0.12) [0.12:1.00] {8}
INTERCHANGE (INT)	0.06 (0.02) [0.00:0.24] {17}	REGRESSION_SR	0.26 (0.04) [0.00:0.90] {39}
TOTAL CAR COST (TC)	0.22 (0.03) [0.05:0.79] {38}	REGRESSION_LR	0.42 (0.05) [0.10:1.74] {48}
HEADWAY	0.10 (0.02) [0.00:0.43] {36}	REGRESSION_ND	0.20 (0.01) [0.03:1.20] {190}
PARKTIME	1.11 (0.29) [0.82:1.40] {2}	FOURSTAGE	0.40 (0.04) [0.00:2.78] {202}
RESTCOST	0.10 (0.03) [0.00:0.49] {24}	CHOICE_RP	0.15 (0.01) [0.00:1.40] {233}
MODE AFFECTED AND ALTERED		CHOICE_SP	0.29 (0.04) [0.03:0.82] {49}
CAR_BUS	0.08 (0.01) [0.00:0.77] {85}	CHOICE_RPSP	0.14 (0.03) [0.02:1.31] {51}
CAR_RAIL	0.09 (0.01) [0.00:0.75] {88}	OBSERVED	0.32 (0.10) [0.09:0.80] {7}
CAR_LRT	0.04 (0.02) [0.01:0.13] {6}	PERIOD INTERACTIONS	
CAR_METRO	0.24 (0.13) [0.02:0.55] {4}	REG_LR_LONGER	0.51 (0.09) [0.10:1.74] {26}
CAR_AIR	0.03 (0.01) [0.01:0.08] {10}	REG_SR_LONGER	0.24 (0.05) [0.00:0.90] {26}
CAR_PT	0.06 (0.01) [0.01:0.59] {58}	REG_ND_LONGER	0.26 (0.03) [0.02:1.20] {141}
BUS_RAIL	0.31 (0.04) [0.02:1.31] {63}	SOURCE	
BUS_LRT	0.20 (0.04) [0.05:0.38] {8}	JOURNAL	0.26 (0.02) [0.00:2.78] {342}
BUS_METRO	0.16 (0.00) [0.16:0.16] {1}	CONFERENCE	0.23 (0.02) [0.00:1.80] {254}
BUS_AIR	0.01 (0.00) [0.00:0.02] {10}	PUBLISHED	0.18 (0.02) [0.00:1.57] {183}
BUS_CAR	0.26 (0.03) [0.00:1.43] {121}	UNPUBLISHED ACADEMIC	0.26 (0.03) [0.00:2.11] {180}
LRT_CAR	0.14 (0.04) [0.00:0.54] {14}	UNPUBLISHED CONSULTANCY	0.28 (0.02) [0.00:1.30] {137}
LRT_BUS	0.17 (0.03) [0.03:0.28] {9}	JOURNEY LENGTH	
LRT_RAIL	0.02 (0.01) [0.01:0.06] {5}	URBAN	0.16 (0.01) [0.00:1.40] {429}
RAIL_CAR	0.33 (0.02) [0.02:0.18] {211}	INTER	0.27 (0.02) [0.00:1.80] {314}
RAIL_BUS	0.18 (0.02) [0.01:0.91] {68}	LONG	0.17 (0.03) [0.00:1.74] {79}
RAIL_LRT	0.06 (0.02) [0.02:0.11] {6}	INTER_METRO	0.20 (0.05) [0.00:0.81] {25}
RAIL_AIR	0.21 (0.05) [0.03:0.48] {10}	SUBURBAN_METRO	0.22 (0.03) [0.00:0.44] {34}
METRO_CAR	0.14 (0.06) [0.02:0.39] {7}	ALL_LENGTHS	0.41 (0.04) [0.00:2.78] {215}
METRO_BUS	0.21 (0.00) [0.21:0.21] {1}	AGGREGATION	
METRO_RAIL	0.10 (0.00) [0.10:0.10] {1}	FLOW	0.31 (0.03) [0.00:1.74] {113}
AIR_CAR	0.18 (0.04) [0.00:0.74] {20}	NATIONAL	0.30 (0.02) [0.00:2.78] {433}
AIR_BUS	0.01 (0.00) [0.00:0.02] {10}	REGIONAL	0.25 (0.03) [0.00:0.73] {60}
AIR_RAIL	0.31 (0.06) [0.02:1.74] {33}	URBAN	0.16 (0.01) [0.00:1.40] {363}
WALK_CAR	0.31 (0.12) [0.02:0.84] {9}	INTERNATIONAL	0.11 (0.02) [0.02:0.37] {22}
WALK_BUS	0.01 (0.01) [0.00:0.02] {5}	METROPOLIS	0.04 (0.01) [0.01:0.11] {12}
WALK_RAIL	0.00 (0.00) [0.00:0.00] {5}	OTHER	0.29 (0.03) [0.00:1.20] {93}
WALK_LRT	0.01 (0.01) [0.00:0.03] {5}	WORLD AREA	
WALK_PT	0.06 (0.01) [0.03:0.09] {8}	EUROPE	0.27 (0.01) [0.00:2.78] {814}
CYCLE_CAR	0.34 (0.11) [0.08:0.80] {8}	ASIA	0.22 (0.04) [0.02:0.19] {18}
CYCLE_BUS	0.06 (0.01) [0.02:0.08] {6}	AUSTRALIA/NEW ZEALAND	0.14 (0.02) [0.00:0.80] {107}
CYCLE_RAIL	0.03 (0.02) [0.00:0.12] {6}	NORTH AMERICA	0.18 (0.02) [0.00:1.40] {157}
CYCLE_LRT	0.05 (0.01) [0.01:0.10] {5}	MODE SHARE	
CYCLE_PT	0.12 (0.02) [0.05:0.24] {8}	EVIDENCE	0.21 (0.01) [0.00:1.74] {343}
PT_CAR	0.46 (0.05) [0.00:2.78] {182}	CORRESPONDING AUTHOR	0.28 (0.02) [0.00:2.78] {425}
DEMAND MEASURE		DATABASES	0.26 (0.03) [0.00:2.11] {169}
TRIPS	0.22 (0.01) [0.00:1.91] {758}	'GUESSTIMATES'	0.19 (0.02) [0.00:1.40] {159}
PASS KM	0.31 (0.03) [0.00:2.78] {338}		

Note: Figures are mean elasticity, (standard error of mean), [minimum:maximum] and {number of observations}.

Considerable efforts were made to assemble evidence on V_j/V_i given its critical importance. Fearnley et al. (2017) pointed out that cross-elasticity estimates can be obtained from studies which do not provide any mode share information, particularly where cross-elasticities are not the main focus of the study. Only 343 (31%) of the cross-elasticities could be assigned market shares on the basis of the evidence in the report. The absence of market share information was addressed in a number of ways. Firstly, the corresponding author was contacted. This provided market share evidence for 425 (39%) cross-elasticities, although of course some of these might have been 'guesstimates'. Where this evidence was not forthcoming, online databases were searched for mode share information. This included EPOMM's Modal Split Details[4], UITP's Mobility in Cities Database, and the Australian Government's Bureau of Infrastructure, Transport and Regional Economics' (BITRE) urban passenger transport statistics as well as the UK National Travel Survey. This procedure provided market share data for a further 169 (15%) cross-elasticities. For the remaining 159 (15%) cross-elasticity estimates, a light-touch 'Delphi survey' was employed in which three of the co-authors and two external experts provided their educated 'guesstimates', along with their degree of confidence, for each cross-elasticity estimate based on the available background information. The certainty score was used to calculate weighted average likely mode shares for each observation.

The year of data collection was also recorded, with the midpoint used in the case of time-series data. The year of data collection formed the basis of the GDP per capita figure in purchase power parity US dollars.

3.3 Summary Cross-Elasticity Evidence

Table 5 reports summary cross-elasticity values for the combinations of the mode affected, the mode altered and the attribute[5]. Where the sample sizes become small, the reported mean value is for all or other remaining attributes.

As far as modal effects are concerned, the cross-elasticities for car demand tend to be low; indeed, all the reported means are less than the overall mean of 0.24. In contrast, the cross-elasticities of both bus and rail with respect to car are relatively large and mainly above 0.24, although this is not so for light rail and metro. This pattern of cross-elasticities reflects the general dominance of car mode share. Variation in rail attributes tend to have a larger impact on bus demand than do changes in bus on rail demand.

The cross-elasticities indicate that there is close to no competition between air and bus, in contrast with the cross-elasticities indicating quite strong interactions between air and rail. The competition between air and car is mixed; variations in car have much larger impacts on air than variations in air have on car, presumably reflecting relative market shares.

[4] http://www.epomm.eu/tems/result_cities.phtml?more=1
[5] We have switched the Vehicle Miles (VM) cross-elasticities to be positive for ease of interpretation and in anticipation of the modelling where logarithms are taken.

Turning to the attributes, in two thirds of cases the JT cross-elasticity exceeds that for IVT, which is to be expected, and the JT and IVT cross-elasticities typically exceed the price cross-elasticities even for bus users who might be deemed relatively price sensitive. The headway cross-elasticities tend to be somewhat lower than the JT and IVT elasticities which is in line with the evidence for equivalent own-elasticities (Wardman, 2012) and with headway forming a lower proportion of generalised cost than JT and IVT.

We would conclude that there are only a few clear patterns in the results in Table 5, which might be a function of confounding effects or the inherent variability of cross-elasticities. Superimposing other influential variables would not necessarily provide clearer insights, particularly since it would further stratify samples. This is where meta-analysis of the data in its entirety and seeking to identify and quantify key relationships has attractions. The attractions of meta-analysis have been discussed elsewhere (Button, 1995; Wardman, 2012; Elvik, 2018) and are not repeated here except to say that some have offered a cautionary note (Goodwin et al., 2004; Hensher, 2008; Button, 2018). It is to such meta-analysis that we now turn.

Table 5: Summary of Cross Elasticity Values

Mode Affected	Mode Altered						
	Car	Bus	Rail	LRT	Metro	Air	PT
Car	-	Fare 0.08 (0.013) [41] IVT 0.18 (0.073) [11] JT 0.04 (0.013) [10] Wait 0.10 (0.051) [7] Head 0.04 (0.027) [6] Other 0.03 (0.008) [10]	Fare 0.08 (0.021) [37] IVT 0.11 (0.044) [17] JT 0.14 (0.027) [12] Head 0.06 (0.035) [9] Other 0.07 (0.028) [13]	All 0.04 (0.019) [6]	All 0.23 (0.13) [4]	Fare 0.04 (0.011) [5] Other 0.02 (0.004) [5]	Fare 0.06 (0.020) [33] VM 0.03 (0.011) [12] JT 0.06 (0.012) [10] IVT 0.05 (0.010) [3]
Bus	Fuel 0.19 (0.019) [72] TC 0.19 (0.032) [17] IVT 0.32 (0.057) [14] JT 0.63 (0.126) [10] Other 0.43 (0.161) [8]		Fare 0.28 (0.052) [28] IVT 0.25 (0.068) [10] JT 0.65 (0.114) [10] Head 0.15 (0.053) [6] Other0.21 (0.104) [9]	All 0.20 (0.043) [8]	Fare 0.16 (0.0) [1]	Fare 0.01 (0.004) [5] JT 0.01 (0.003) [5]	
Rail	Fuel 0.27 (0.019) [137] Park Cost 0.08 (0.028) [19] IVT 0.44 (0.073) [15] TC 0.29 (0.042) [15] Fuel Eff 0.75 (0.129) [12] JT 0.94 (0.145) [10] Other 0.30 (0.040) [3]	Fare 0.15 (0.036) [29] IVT 0.29 (0.05) [13] JT 0.24 (0.091) [10] Head 0.09 (0.017) [10] Other 0.13 (0.038) [6]		All 0.06 (0.017) [6]		Fare 0.28 (0.081) [5] JT 0.15 (0.037) [5]	
LRT	Fuel 0.15 (0.044) [12] Other 0.08 (0.015) [2]	Fare 0.21 (0.036) [5] Other 0.12 (0.046) [4]	All 0.02 (0.010) [5]				
Metro	Fuel 0.14 (0.057) [7]	Fare 0.21 (0.0) [1]	Fare 0.10 (0.0) [1]				
Air	Fuel 0.14 (0.035) [7] TC 0.12 (0.053) [5] JT 0.34 (0.111) [5] IVT 0.14 (0.066) [3]	Fare 0.01 (0.002) [5] JT 0.01 (0.004) [5]	Fare 0.18 (0.024) [13] IVT 0.63 (0.198) [8] JT 0.35 (0.059) [5] Head 0.17 (0.073) [5] Other 0.11 (0.077) [2]				
Walk	Fuel 0.11 (0.029) [4] Other 0.47 (0.182) [5]	All 0.014 (0.004) [5]	All 0.0 (0.0) [5]	All 0.01 (0.005) [5]			All 0.06 (0.008) [8]
Cycle	All 0.34 (0.115) [8]	All 0.06 (0.010) [6]	All 0.03 (0.018) [6]	All 0.05 (0.015) [5]			All 0.12 (0.022) [8]
PT	Fuel 0.28 (0.037) [124] IVT 0.86 (0.087) [57] TC 0.01 (0.00) [1]						

Note: Figures reported are mean, (standard error) and [number of observations].

4. META-ANALYSIS OF CROSS-ELASTICITY DATA

We here report the quantitative, regression based, analysis which aims to explain variations in cross-elasticities across studies by reference to a range of key influential variables. In the process, we address issues of a methodological nature concerning how cross-elasticities are estimated and explore inter-temporal variations, areas where this approach is well-placed to provide valuable insights not always possible by other means. Once we have arrived at estimated relationships that are empirically justified and we are comfortable with, we demonstrate the usefulness of the meta-model by 'forecasting' what cross-elasticities would be for a range of illustrative circumstances.

4.1 Method of Analysis

The explanation of variations in cross-elasticities across studies is here based on regression analysis. Given a mix of continuous and categorical variables, the standard regression model used to explain variations in cross-elasticities (CE) could take the following forms:

$$CE = \tau \prod_{i=1}^{n} X_i^{\alpha_i} e^{\sum_{j=1}^{p} \sum_{k=1}^{q_p - 1} \beta_{jk} Z_{jk}} \tag{2}$$

$$CE = \kappa + \sum_{i=1}^{n} \gamma_i X_i + \sum_{j=1}^{p} \sum_{k=1}^{q_p - 1} \lambda_{jk} Z_{jk} \tag{3}$$

where there are n continuous variables (X_i) and p categorical variables having q_p categories (Z_{jk}). We specify q_p-1 dummy variables for a categorical variable of q_p categories and their coefficient estimates are interpreted relative to the arbitrarily omitted base category.

In the multiplicative model of equation 2, the α_i are interpreted as elasticities and the exponential of a β_{jk} denotes the proportionate effect on CE of a particular category relative to its omitted category. In the additive model of equation 3, the γ_i indicate the impact of a one unit change in X_i on CE and the λ_{jk} denote the additive effect of a particular category relative to the base category.

The categorical dummy variable term (Z_{jk}) can represent various studies in our dataset that provide more than one observation[6]. It is prudent to consider such 'study-specific effects' since it is clearly not feasible to assemble data on all factors that might have influenced the cross-elasticities estimated in a specific study. These could be genuine but otherwise omitted effects, representing a study in, say, a wealthy locality, or the use of short run rather than long run own-elasticities to deduce cross-elasticities, but they might not be, such as discerning the consequences of a lesser

[6] There is no difference between a model which removes a study with one observation and one which retains it but with a study-specific dummy variables.

quality study or the poor specification of some variable such as study-specific market shares. Either way, we would rather identify and isolate their effects rather than risk them impacting upon the main coefficient estimates.

A more parsimonious way of discerning such study-specific effects is to estimate a random effects model which assumes that all the study related unobserved heterogeneity can instead be represented by an additional error term related to the studies.

A further consideration is that whilst equation 3 can be directly estimated by ordinary least squares, the multiplicative model of equation 2 cannot. Two means of estimating the parameters of equation 2 are explored. One is the standard approach of taking a logarithmic transformation, whereupon the parameters can be estimated by ordinary least squares, and the other approach is to estimate the parameters directly using non-linear least squares.

4.2 Comparison of Different Meta-Model Formulations

As will be apparent from the previous discussion, four models have been explored[7]:

- Model Type I: Multiplicative model estimated as a logarithmic transformation of equation 2.
- Model Type II: As Model I but with direct estimation of the parameters of equation 2.
- Model Type III: Additive model as represented by equation 3.
- Model Type IV: A random effects multiplicative model.

Identification of what has become our preferred model was an iterative process that involved a considerable number of estimations. We initially explored the standard multiplicative model estimated as a logarithmic transformation of equation 2 (Model I) since this is a common formulation of econometric models in transport and indeed it dominates previous meta-analyses.

At the outset, an issue to address with this functional form is the treatment of the 53 (4.8%) zero cross-elasticities in our sample of 1096. It is clearly unacceptable to simply remove them[8]. Some of the zero cross-elasticities assembled will have resulted from rounding, particularly the 45% of them that were deduced, and hence using some low value instead of zero would seem justified. We experimented with various low positive values as replacements for the zeros; the variations in the parameter estimates and goodness of fit were negligible and we settled upon a value of 0.0025. Furthermore, Model II can handle zero cross-elasticities and replacing the 53 zeros with 0.0025 resulted in a mean absolute variation across all the coefficient estimates of only 0.003!

A wide range of variables were tested, both as main effects and interactions, settling upon an initial set of retained variables. We then investigated study-specific effects, commencing by suppressing

[7] There is more emphasis here on comparing a range of model forms than in the previous meta-analysis studies discussed below.

[8] However, we have to accept that low cross-elasticities are more likely to be removed from reported models as not statistically significant and hence will be under-represented.

the constant term and specifying the full set of 77 dummy variables for studies that contained more than one observation. This indicated that study 39 was 'average' and this was subsequently used as the arbitrarily omitted base category whereupon the study-specific effects denote how each departs from the average. We then progressively removed those with the lowest t ratios, continuing until those significant at the 5% level remained.

When we arrived at this model, we returned to the main independent variables and removed those that were now insignificant and explored whether previously omitted variables become significant when re-instated. This led to only a few amendments, whereupon we tested whether the more significant of the previously omitted study-specific variables became significant and removed any that were no longer significant, again with few modifications.

We are confident from the many models estimated that we have arrived at a combination of main and study-specific effects that are jointly significant. This is our preferred Model I. It is statistically superior to the corresponding model that does not contain the study-specific effects given an F statistic of 17.57 compared to a critical value at 5% significance of around 1.6 for (20, 1038) degrees of freedom. It is also superior to the model containing the full set of 77 study-specific terms given an F statistic of 1.17 which for (56,982) degrees of freedom is less than the critical value of around 1.35. We can in any event point to similarities in the coefficient estimates regardless of the number of study-specific effects. On average, the model with no study-specific effects returns main coefficient estimates that are on average only 4% larger than for Model I whilst the corresponding figure for the model with the full set of study-specific effects is only 5% lower.

Model I turned out be that preferred from amongst the four set out above and is reported in Table 6 and discussed in detail in section 4.3. We now discuss how we arrived at this preference over Models II, III and IV whose details are reported in the Appendix. The latter all contain the same independent variables for ease of comparison except for Model IV where a random effect related to study replaces the study-specific dummy variables.

The additive formulation of Model III has an adjusted R^2 of 0.417 which is less than the 0.483 for the directly estimated multiplicative formulation of Model II for the same dependent variable. The additive formulation can therefore be discounted.

Model I and Model II are the two versions of equation 2 which differ in terms of whether the error term is additive or multiplicative. When the appropriate adjustment is made to compare the goodness of fit measures (Gujarati, 2009), given the dependent variables are different, Model I has a revised adjusted R^2 of 0.603 which is better than the 0.483 for the directly estimated Model II. Furthermore, Model I provides coefficient estimates that are generally far more significant, with average t ratios of 5.6 compared to 2.5 for Model II and all 58 coefficient estimates significant at the 5% level compared to only 28 in the latter model. Model I is therefore preferred to Model II.

The remaining comparison is of Model I with the random effects formulation of Model IV. The latter achieves a much lower adjusted R2 of 0.521 for the same dependent variable. Nonetheless, the coefficient estimates of Model IV are on average only 16% different from Model I. More formally, a Hausman test comparing model IV with a full fixed effects specification causes us to reject the null hypothesis that random effects is preferred in favour of a fixed effects model ($p < 0.004$). Further modifications of Model IV to include study specific effects show only a very small increase in adjusted R^2 and no substantial variation in the parameter estimates.

4.3 Discussion of Preferred Model

Model I is our preferred formulation for a more detailed discussion of the extent to which a range of influential variables impacts on cross elasticities, and it is to this discussion of the results presented in Table 6 that we now turn.

Diagnostic Features

At the outset of this modelling process, we did not anticipate being able to detect very many significant effects given the inherent variability of cross-elasticities and the challenges of estimating them. We therefore consider it impressive that we have been able to recover such a large number of statistically significant effects which generally seem credible. In part, the large data set of 1096 observations will have helped, extending considerably on the 171 in the cross-elasticity meta-analysis reported by Fearnley et al. (2018). Our sample compares favourably with the 444 observations for one of the first meta-analyses of value of time (Wardman, 1998)[9], the 258 for the first meta-analysis of noise valuations (Bristow et al., 2015), and the samples of 1633 and 427 for the most extensive meta-analyses of price elasticities (Wardman, 2014) and time based elasticities (Wardman, 2012) respectively. The Hensher (2008) meta-analysis of a range of elasticities covered 319 observations whilst Holmgren (2007) assembled 186 public transport demand elasticities covering five variables and Kremers et al. (2002) identified 76 price elasticities. Espey (1998) reported one of the first transport meta-analyses and covered 640 fuel price elasticities whilst Brons et al. (2002) was restricted to 204 air travel price elasticities.

Given that cross-elasticities are variable and not always estimated with a great deal of precision, we find the adjusted R^2 of 0.633 to be very encouraging[10]. Indeed, it compares favourably with other meta-analysis models having the same logarithmic functional form. For example, the most recent value of time meta-analysis (Wardman et al., 2016) covering European wide evidence obtained an adjusted R^2 of 0.70[11] and the meta-analyses of price elasticities (Wardman, 2014) and of time-related elasticities (Wardman, 2012) both recovered adjusted R^2 values of 0.64. Notably though, the noise valuation meta-analysis of Bristow et al. (2015) achieved a figure of 0.86 even though these are intrinsically variable valuation estimates. The meta-analysis of cross-elasticities between public

[9] Subsequent published UK meta-analysis studies increased this to 1116, 1167 and 1749.
[10] This increased to 0.741 when outliers were omitted.
[11] As opposed to 0.78 when outlier observations were removed

transport modes reported in the predecessor paper of Fearnley et al. (2018) recovered an adjusted R^2 of 0.43. Studies that specified linear-additive functions, where the goodness of fit is not directly comparable, achieved adjusted R^2s of between 0.12 and 0.34 (Hensher, 2008), 0.27 (Kremers et al., 2002), between 0.22 and 0.68 (Holmgren, 2007), 0.43 (Brons et al., 2002) and between 0.28 and 0.34 (Espey, 1998).

Table 6: Estimated Parameters of Model I

	Variable	Coeff (t)	Effect		Variable	Coeff (t)	Effect
	CONSTANT	-2.876 (16.4)		Journey Purpose including Interactions with Distance and Attribute Base = Leisure	BUSINESS	-0.426 (2.6)	*0.65
Attribute Base = fuel	FARE	0.633 (6.2)	*1.88		BUSINESS_LONG	-1.242 (3.4)	*0.29
	IVT	0.895 (8.6)	*2.45		BUSINESS_TIME	0.722 (3.4)	*2.06
	ACCEGR_TRANSFER	0.726 (4.8)	*2.07		LEISURE_TIME	0.359 (3.6)	*1.43
	JT	0.833 (6.0)	*2.30	Distance Base = Urban	LONG	-1.498 (8.9)	*0.22
	PARKTIME	2.757 (7.8)	*15.75	Relative Demand	LN_DEMAND_RATIO	0.355 (16.1)	[A]
	RESTCOST	-1.077 (4.2)	*0.34	Time Trend	TREND_TIME	-0.018 (4.8)	*0.98
Modal Combinations including distance interactions Base = Car_Bus	BUS_RAIL	0.777 (4.6)	*2.18		TREND_PRICE	-0.015 (4.5)	*0.98
	BUS_LRTMETRO	1.221 (5.3)	*3.39	Study-Specific Effects	Study1 (12)	-1.266 (8.8)	*0.28
	BUS_AIR	-2.421 (6.9)	*0.09		Study2 (5)	-2.257 (4.2)	*0.10
	BUS_CAR	0.565 (3.8)	*1.76		Study3 (6)	1.574 (5.8)	*4.82
	LRT_CAR	1.222 (2.7)	*3.40		Study6 (10)	0.988 (3.2)	*2.68
	LRTMETRO_BUS	0.853 (3.6)	*2.35		Study12 (34)	-2.037 (5.8)	*0.13
	RAIL_CAR	0.904 (5.5)	*2.47		Study17 (5)	-1.762 (6.2)	*0.17
	RAIL_BUS	0.851 (7.7)	*2.34		Study18 (4)	-1.460 (2.0)	*0.23
	RAIL_AIR	1.460 (4.8)	*4.30		Study24 (14)	-1.146 (7.3)	*0.32
	AIR_BUS	-2.608 (11.6)	*0.07		Study25 (2)	1.672 (2.4)	*5.32
	AIR_RAIL	1.590 (8.8)	*4.90		Study26 (48)	-0.617 (5.5)	*0.54
	WALK_BUSRAILPTLRT	-1.084 (6.4)	*0.34		Study51 (5)	-1.169 (5.0)	*0.31
	CYCLE_RAIL	-1.221 (4.9)	*0.30		Study55 (2)	2.405 (4.0)	*11.08
	PT_CAR	0.788 (5.8)	*2.20		Study58 (3)	1.906 (4.5)	*6.73
	BUS_RAIL_INTER	0.555 (2.7)	*1.74		Study63 (8)	-1.025 (2.8)	*0.36
	CAR_RAIL_INTER	1.033 (8.7)	*2.81		Study65(36)	0.818 (6.9)	*2.27
	RAIL_CAR_INTER	0.773 (5.2)	*2.17		Study66 (22)	1.587 (5.1)	*4.89
Estimation Method Base = Deduction	REGRESSION_CROSS	1.264 (4.2)	*3.54		Study74 (7)	-1.228 (3.2)	*0.29
	REGRESSION_LR	0.855 (6.0)	*2.35		Study78 (8)	-1.470 (3.5)	*0.23
	REGRESSION_ND	0.188 (2.0)	*1.21		Study86 (12)	-1.369 (5.6)	*0.25
	FOURSTAGE	0.381 (3.2)	*1.46		Study93 (7)	0.905 (5.1)	*2.47
	CHOICE_SP	1.229 (7.3)	*3.42	Goodness of Fit	ESS / RSS	1815.04 / 968.68	
	OBSERVED	1.271 (6.7)	*3.56		Adj R^2	0.633	

Note: Figures in brackets for each study denote the number of cross-elasticities it contained. The effect column is the exponential of the coefficient estimate and denotes the multiplicative effect on the cross-elasticity of the variable in question. [A] The coefficient for *LN_DEMAND_RATIO* is an elasticity.

Whilst all of the coefficient estimates are significant at the widely used 5% level, more noteworthy is that 48 (83%) of the 58 coefficient estimates are significant at the 0.1% level of significance.

Since there are so many parameters in our estimated models, a natural concern would be that there are inevitably many large correlations of estimated coefficients which might then cast reservations upon the robustness of the relevant estimates and be suspected to cause an inflated goodness of fit.

Of the 1653 pairwise correlations of estimated coefficients, it is very encouraging that only four exceeded 0.6. These were *TREND_TIME* and the constant term (-0.77), *TREND_PRICE* and the constant (-0.72), *BUS_RAIL* and *BUS_RAIL_INTER* (-0.66), and *RAIL_CAR* and *BUS_CAR* (0.64). Indeed, very few were greater than 0.3.

Looking beyond pairwise correlations, tolerance parameters can be estimated for each coefficient estimate to determine if multicollinearity across the full set of included variables is an issue. This involves multiple regression of each independent variable on all other independent variables. For each variable, the term $1-R^2$ is referred to as the tolerance level, where R^2 is the specific regression goodness of fit. Whilst as with pairwise correlations there is no formal value that indicates a problem, a tolerance level less than 0.2 is considered to indicate strong multicollinearity (O'Brien, 2007). In our dataset, the only tolerance levels less than 0.2 were for *TREND_TIME* (0.12) and *TREND_PRICE* (0.15). This is in line with the pairwise correlations and we return to this below.

High levels of collinearity amongst coefficient estimates is a problem that has to be lived with when it occurs; thankfully, despite so many coefficient estimates, we conclude that it is not here a cause for particular concern.

The presence and impact of heteroscedasticity was also tested. We used the weighted estimation routine in SPSS which estimates a series of models where the observations are weighted by $1/W^{\lambda}$ across a pre-specified range of λ and the value of λ is identified which maximises the log-likelihood function. Using the cross-elasticity itself as W recovered a λ of -0.35. The adjusted R^2 fell to 0.594 but the coefficient estimates in the weighted model differed only by 3.1% on average and the t ratios were only 2.9% lower on average. We experimented with using year of data collection, the relative demand of the altered and affected modes and the number of cross-elasticity observations per study and each provided lower values of λ with on average negligible impacts on coefficient estimates and t ratios.

We opted for the White standard errors in SAS that are heteroscedasticity consistent (White, 1980). This procedure does not impact on the coefficient estimates or the adjusted R^2; the t ratios are on average 22% larger than otherwise although making no difference to what is significant at the 5% level.

We now discuss in turn the results for variables which were found to have a significant effect on cross-elasticities. Main effects as indicated in Table 4 that were examined but were not statistically significant at the usual 5% level were the source of the evidence, the level of aggregation, country and world area, the functional form used to estimate cross-elasticities in demand models, the level of GDP and the demand measure. Nor did the number of cross-elasticities per study have any effect.

Attribute Type

The base attribute was initially *FUEL.* The coefficient estimate for total car cost was found to be insignificant when it should indicate a larger cross-elasticity than for fuel given that the latter forms only a proportion of total car cost. We presume that a contributory factor here is that fuel is the main cost determinant of car travel and other costs are either ignored or misperceived. The coefficients for Wait time, *VM*, the number of interchanges and headway were also insignificant. Whilst transfer time was marginally insignificant, it had a coefficient very similar to the access/egress coefficient and hence the variables were merged (*ACCEGR_TRANSFER*).

Fare cross-elasticities, all else equal, are relatively large. Given the base includes and is dominated by fuel price cross-elasticities, this is hardly surprising on the grounds that decisions makers are regarded to take more account of fare costs than fuel costs or total car costs.

The journey time (*JT*) cross-elasticity should exceed the in-vehicle time (*IVT*) cross-elasticity but it is slightly smaller. It may be that JT is itself dominated by *IVT* whilst some studies might have reported what was effectively *IVT* as *JT*. Given that *IVT* and *JT* are essentially the same for car travel, we explored whether the difference between the two cross-elasticities was as expected when public transport modes were altered but no incremental effect was apparent. The multiplicative effects of *IVT* and *JT* on the cross-elasticities are relatively large.

ACCEGR_TRANSFER also has a relatively large cross-elasticity, although lower than for *IVT* and *JT* which might reflect it forming a lower proportion of generalised cost whilst in some cases the variations in these terms can be relatively minor.

PARKTIME has very large cross-elasticities, although this relates to only two observations and too much should not be made of this effect. Cross-elasticities for *RESTCOST* are lower than for fuel cost. This is perhaps unsurprising given that it largely relates to parking cost and not everyone pays to park.

It is not always clear whether fuel cost cross-elasticities took into account for fuel efficiency. Given that fuel efficiency varies over time, we tested whether the *FUEL* cross-elasticity was different when estimated to time-series data but there was no significant effect.

Modal Combinations

Cross-elasticities measure the degree of competition between specific modes and hence the appropriate terms are the combination of the mode impacted and the mode altered rather than mode impacted and mode altered separately.

Whilst market shares vary by mode, and our investigation of this issue is discussed below, equation 1 indicates that cross-elasticity variation is not just dependent upon market share variation and hence additional modal effects are permissible and their investigation warranted.

Our data set contains 35 modal combinations and, as is clear in Table 4, some have very few observations. We therefore combined *CAR_LRT* and *CAR_METRO, BUS_LRT* and *BUS_METRO*, *LRT_BUS* and *METRO_BUS*, and *LRT_RAIL* and *METRO_RAIL*, given that Metro and LRT are not dissimilar. We also merged the small samples of walk as an affected mode and the four public transport altered modes. As such there are 28 modal combination categories, and coefficient estimates for 14 of these are reported in Table 6.

The base category was *CAR_BUS*. Relative to this, the modal combinations of *CAR_RAIL* and *CAR_PT* were not significant despite large sample sizes. This is presumably because they each offer broadly similar competition to car which is also why the combined *CAR_LRT* and *CAR_METRO* segment was not significant. *CAR_AIR* was also insignificant but based on a small sample size. Given that car is seen by many as a very attractive means of transport, it is not surprising that most other cross-elasticities in Table 6, all else equal, are larger.

Turning to bus as the affected mode, there are significant incremental effects for all categories of Table 4. The competition from rail on bus is larger than for car on bus, as might be expected, and around twice that of the base category of *CAR_BUS*. We would expect LRT and METRO to be here providing stronger competition to bus than rail and car and this is apparent in the much larger incremental effect. Competition from air on long distance bus is very weak and this is not surprising.

The *LRT_CAR* cross-elasticity is one of the largest, all else equal, whilst bus is also providing strong competition to LRT. *LRTMETRO_Rail* was insignificant, which may reflect the fact that rail networks are often remote from light rail and metro networks.

The one rail affected cross-elasticity that was not significant was *RAIL_LRT,* reflecting the generally weak competition between these two modes but also perhaps the small sample size. Compared to the base of *CAR_BUS*, the *RAIL_CAR* and *RAIL_BUS* cross-elasticities are much larger. Where rail and air are available, there is particularly strong competition from air on rail (*RAIL_AIR*).

The only separate term for Metro as an impacted mode is for the competition from car (*METRO_CAR*) and this was not significant. This contrasts with other cross-elasticities where car is the altered mode and may be because where it exists Metro is in a strong competitive position relative to car.

There are three categories of air as an affected mode. We see, not unexpectedly, that there is little competition from bus on air (*AIR_BUS*), and indeed it is the lowest of our cross-elasticities, slightly lower than *BUS_AIR*. *AIR_CAR* was not significant but, in line with the strong competition implied by

RAIL_AIR, rail has a very strong impact on the demand for air travel (*AIR_RAIL*). The latter finding may reflect the investigation of high speed rail which can compete well with air travel.

There was no impact from car on walking (*WALK_CAR*) relative to the base. However, the public transport modes offer even less competition to walking (*WALK_BUSRAILPTLRT*). As for cycling, the categories have few observations and combining them did not help matters. Only one significant effect was obtained, relating to *CYCLE_RAIL* which indicates a very low cross-elasticity which is hardly surprising given that rail tends to cater for longer distance urban trips. The *PT_CAR* effect is in line with the *BUS_CAR* and *RAIL_CAR* effects.

In addition to the modal combinations, for the main modes of car, bus and rail, where rail also here included the other rail-based modes, terms were specified solely for the mode affected and the mode altered. Of these six incremental effects, the only one that was near to significant, with a t ratio of 1.2, was that cross-elasticities for car as the mode impacted was 27% lower. These terms were therefore not retained. We find it reassuring that there were no additional significant mode impacted or mode altered affects over and above the modal combination effects. We also explored whether the modal effects varied by whether the cross-elasticity was price or time-based but none were significant.

Whether the modal combination effects varied with distance was also investigated. Metro, LRT, PT, walk and cycle are specific to short distance whilst air is specific to long distance. We therefore allowed the cross-elasticities involving combinations of bus, rail and car to vary with distance band. The best specification was for INTER excluding LONG[12].

The interactions involving bus and car were not significant, which is perhaps unsurprising given that analysis of the longer distance bus market is not common whereupon there are few observations and this might have contributed to the absence of a significant incremental effect on *RAIL_BUS*. We did though recover three significant incremental effects for inter-urban travel in line with our expectation that competition between modes is stronger for less routinely/habitually made inter-urban trips which tend to involve significantly greater time and cost commitments.

Cross elasticities between bus and rail (*BUS_RAIL_INTER)* are around 70% larger but it is car and rail which become noticeably closer substitutes in the inter-urban market with cross-elasticities 117% larger for rail and car (*RAIL_CAR_INTER*) and 181% larger for car and rail (*CAR_RAIL_INTER*). It was also hypothesised that there is more consideration of fuel costs for longer distance journeys but there was no significant incremental fuel price effect.

When we removed the demand share variable (*LN_DEMAND_RATIO*) the adjusted R^2 falls considerably, from 0.633 to 0.550, indicating that the modal combinations cannot of themselves discern the impact on cross-elasticities otherwise attributed to variations in demand share.

[12] As discussed in section 3.2, long is inter-urban where air is relevant.

Estimation Method

The base was taken to be the method of deduction using equation 1. Turning first to the regression based approaches, *REGRESSION_SP* was not significant but then it only relates to 16 observations. *REGRESSION_CROSS* relates to even fewer observations but is though significant. It noticeably has a large incremental effect, indeed the second largest of all the estimation methods. Whilst this is in line with the widely held view that such cross-sectional models recover inflated elasticities because of their failure to distinguish cause and effect, we would not expect such simultaneity to relate to the attributes of other modes. There is also a widely held view that cross-sectional models recover long run effects. Nonetheless, this is not a mainstream method and having isolated its effect it can be ignored.

Of much more importance are the regression results based on the more widely accepted analysis of data with a time series dimension[13]. *REGRESSION_LR* has a larger impact than *REGRESSION_ND* which in turn is larger than the insignificant and hence omitted *REGRESSION_SR*. These relationships are consistent with expectations, with the long run cross-elasticities 2.35 times the short run cross-elasticities. This is broadly in line with a ratio in the range 1.7 to 2.0 for own-price elasticities in the meta-analysis of Wardman (2014) and the range 1.9 to 2.4 for own-time elasticities in the meta-analysis of Wardman (2012).

We note that the insignificance of the *REGRESSION_SR* term implies correspondence with the *DEDUCED* cross-elasticities. This would seem to indicate that, in general, the deduced method of equation 1 used own-elasticities more akin to short run than long run. With hindsight we should have identified whether the deduced method used short-run, non-defined or long-run cross-elasticities, although it would not have been readily apparent in all cases.

FOURSTAGE has an effect between the long run and short run. This seems credible, since such models will include more than just a short term response but they do not explicitly address dynamic behavioural response.

The *CHOICE_RP* and *CHOICE_RPSP* terms were both insignificant, therefore aligning themselves with short run effects from regression based approaches. It seems credible that choice models based on actual behaviour yield short run effects. It is not surprising that *CHOICE_SP* indicates larger cross-elasticities, which are here also somewhat larger than the *REGRESSION_LR* cross-elasticities, given the incentive in purely hypothetical exercises to exaggerate behavioural responses for strategic reasons. In support of this, the Wardman (2014) meta-analysis of own-price elasticities found SP choice based elasticities to be around twice those of equivalent RP values whilst the Wardman (2012) meta-analysis of time based own-elasticities found the ratio to be in the range 25% to 70% larger, although Kremers et al. (2002) and Hensher (2008) are less clear-cut in this regard. In the specific context of cross-elasticities, the Fearnley et al. (2018) meta-analysis reports SP cross-elasticities to be twice the RP equivalents.

[13] Almost all of these were from models with a constant elasticity specification.

The *OBSERVED* method yields what would seem to be an implausibly large incremental effect, although with a very small sample. It is though not a mainstream approach, and it may be that the impacts of other unaccounted for changes at the time have a confounding effect. It is sufficient here that we have isolated the large effect.

For the cross-elasticities obtained from time series regression, a further distinction can be made by the periodicity of the demand data upon which the models were estimated. Three terms were defined (*REG_LR_LONGER*, *REG_SR_LONGER* and *REG_ND_LONGER*) as explained in section 3.2. The cross-elasticities might be expected to be larger where the time period is longer, particularly for short run cross-elasticities, but none of these interactions were significant.

Journey Purpose

We distinguish four journey purposes of commuting, business, leisure and all as discussed in section 3.2. Leisure was taken as the arbitrary base. Surprisingly, given our ability to obtain statistically significant effects for a number of other variables and the importance of journey purpose in transport planning and behavioural analysis, along with the large number of observations for each journey purpose, we were only able to discern an effect for business travel.

BUSINESS was found to have cross-elasticities around two-thirds of other purposes. Whilst business travellers can be reasonably expected to have a lower sensitivity to price, given that the company pays, they might also be expected to be more sensitive to time. We therefore specified interaction effects for the various journey purposes and time-based cross-elasticities.

Business travellers were indeed found to have a greater sensitivity to time variables (*BUSINESS_TIME*) and this very much offsets the *BUSINESS* term. The time-based cross-elasticities were also found to be larger for leisure travel (*LEISURE_TIME*). This is attributed to commuters being more captive to their mode.

The journey purpose effect might vary with journey distance. We therefore specified incremental effects for inter-urban and long distance for each journey purpose. The only significant effect was that those travelling long distance on business had very low cross-elasticities (*BUSINESS_LONG*) and are apparently more captive to their chosen modes.

Journey Length

It can be readily appreciated that cross-elasticities are different between urban and longer distance trips. Urban trips tend to be more routine and involve lower generalised costs, whereby habitual behaviour is more likely, whilst the car is often the overwhelmingly attractive option where available[14] and users of other modes tend to be more captive. In contrast, longer distance trips are

[14] Indeed, many routine urban trips by car would simply not be made if the car was not available.

less frequently made and involve larger investments of time and money, whereupon decisions might have a more considered basis.

Apart from the inter-urban effects on the modal-combination variables (*BUS_RAIL_INTER, CAR_RAIL_INTER, RAIL_CAR_INTER)* and the interaction of business and long distance (*BUSINESS_LONG*), which have already been discussed, the only other significant effect obtained was that long distance trips (*LONG*) have very much lower cross-elasticities. On such trips, different modes are effectively not substitutes for each other, and mode specific factors are key to travel behaviour.

As is apparent in Table 4, we also distinguished both suburban and inter-urban flows that were to major metropolis. No significant effects were discerned for interaction terms for such flows. Whilst the sample sizes are not large, we would point out that on such flows the market shares tend to be very much different, with a stronger performance of public transport and particularly rail, and the relative demand term might be discerning this.

Relative Demand

This is perhaps the most critical variable of all those investigated. It is widely regarded that cross-elasticities are dependent upon market share and indeed equation 1 demonstrates this. The absence of any discernible effect here could be seen as a serious shortcoming of our explanatory model and hence considerable effort was made to ensure that we had market share estimates for the affected and altered modes for each observation in our dataset.

The term *LN_DEMAND_RATIO* is specified as the logarithm of the ratio of the demand of the altered mode and the affected mode. Hence its coefficient estimate should be positive, which it is, and it is estimated very precisely.

Incremental effects were specified to represent where the market share information was subsequently obtained from corresponding authors, databases or as best guesstimates as discussed in section 3.2. The incremental coefficients and t ratios were 0.094 (2.2), 0.047 (0.9) and -0.054 (0.7) respectively, with the base coefficient estimate being 0.261 (6.2). The effects from databases and guesstimates can be discounted as far from significant and it turned out that once these were removed then the corresponding author effect became marginally insignificant. In the light of this, and that the variations anyway are relatively minor, we have not retained any incremental effects and are left with an average across all categories of 0.355 (16.1). The only other evidence we can compare against is Fearnley et al. (2018) which for a broadly comparable model in terms of the inclusion of modal combinations recovered a figure of 0.459 (t=5.9) although the latter related only to competition between public transport modes and has a much larger confidence interval.

We also explored whether the relative demand impact was different for inter-urban and long distance trips but no significant incremental effects were apparent.

Whilst we would expect *LN_DEMAND_RATIO* to equal one if both η_{jj} and δ_{ji} of equation 1 were being accurately discerned elsewhere in the model, this will not be the case. In particular, it might be expected that both η_{jj} and δ_{ji} fall as mode j becomes relatively more attractive and V_j/V_i increases. This would serve to reduce the *LN_DEMAND_RATIO* coefficient to be less than one. A figure of 0.355 seem credible and Table 7 illustrates how different levels of *LN_DEMAND_RATIO* would impact on the implied cross-elasticities.

Table 7: Impact of V_j/V_i Ratio on Implied Cross-Elasticities

DEMAND_RATIO	Multiplier
10	2.26
5	1.77
2.5	1.38
1	1.00
0.4	0.72
0.2	0.56
0.1	0.44

It could be argued that the *LN_DEMAND_RATIO* coefficient is less than one because other variables, and particularly the modal combinations, are also discerning market share effects. However, when we removed all the modal combinations, the *LN_DEMAND_RATIO* coefficient estimate increased only slightly to 0.401 (17.7) but the adjusted R^2 was considerably lower at 0.469.

Time Trends

We have examined whether, all else equal, cross-elasticities vary over time, proxying for inter-temporal influences that we are unable to include in our model. To support this, there is a reasonable spread of cross-elasticities across years; 1961 is the first year in our data set with 16% of observations up to 1990, 29% between 1991 and 2000, 43% between 2001 and 2010, and 12% post 2010[15]. The time trend enters without logarithmic transformation and hence the exponential of its coefficient indicates the annual multiplicative effect on the cross-elasticity.

If there are trend effects, it would seem sensible to allow for differences between time and price based cross-elasticities. Statistically significant negative effects were discerned for both, with the time (price) based cross-elasticities estimated to be falling by on average 1.8% (1.5%) per year.

As far as lower price-based elasticities over time are concerned, this could stem from increasing real incomes. Trends to shorter working weeks, part time working, more labour saving devices and the increasing ability to undertaken worthwhile activities during travel time would contribute to lower time-based cross-elasticities.

[15] The years here relate to the data upon which the cross-elasticities were estimated, as opposed to the year of publication covered in Table 2.

Some though may not find these arguments convincing, and cite the more hectic pace of life, travel conditions being more congested, crowded and unreliable, and a tendency for transport prices to increase in real terms. It should though be pointed out that the estimated trends are not the spurious outcome of the correlations we have noted, since specifying a single time trend recovered a coefficient estimate of -0.016 (5.0) which is between the separate trends for time and price-based cross-elasticities and the tolerance parameter for this term was 0.61.

Another potentially undesirable feature is that the variation is large over the entire period of the data set. Compared to 1961, the 2017 price-based elasticities would be 57% lower and the time-based elasticities would be 64% lower. However, these reductions are much lower, at 23% and 26% respectively, relative to 2000 which would cover around a half of our data.

The model can be used if so desired to predict cross-elasticities without allowing any time trend effect. To do this, the year can be set at its weighted average in the data set, which is 2000 (trend = 40) for both time and price-based cross-elasticities.

Study-Specific Effects

Study-specific effects were specified because there may well be influences on estimated elasticities that we cannot observe or account for. In particular, meta-analysis has been subject to concerns and criticism that the selection of evidence to include has a material impact on the results obtained (Melo et al., 2009; Button, 2018) . The approach taken here is to err on the side of including evidence we have uncovered and then to let the analytical process address matters. This was apparent in our discussion in section 3.1 but critical to 'letting the data decide' is inspection of residuals, which is discussed below, and the inclusion of study-specific dummy variables that we here discuss[16].

Model I contains 20 significant study-specific effects which represent 26% of the 76 eligible studies and 23% of the cross-elasticity observations. The estimated study-specific effects average -0.248 but this falls to -0.094 when weighted by sample size across all 93 studies. Thus a weighted average constant across all studies would equal -2.970[17] and would make very little difference to the cross-elasticities that would be obtained from the estimated model in predictive mode. Nonetheless, it is worth exploring whether these study-specific effects are discerning factors that we should be aware of. 12 studies with few observations can be discounted (Studies 2, 3, 17, 18, 25, 51, 55, 58, 63, 74, 78 and 93), which in any event have a weighted average of -0.04, with a focus on the remaining 8 studies where some interesting observations can be made.

[16] We should point out that we also specified country-specific and area of the world-specific dummy variables but none were significant.
[17] The corresponding model without any study-specific effects returned a constant of -3.211 (18.5).

Study 1 (Acutt and Dodgson, 1996) used equation 1 to deduce cross elasticities. What is notable though is that the results are based on a Delphi survey of diversion factors and market shares. The same method is used in Study 24 (Dodgson, 1986) and the diversion factors were guessed.

Study 6 (ARUP and OXERA, 2010) provided cross elasticities of rail demand with respect to fuel price, distinguishing short and long run and different types of flow. The cross-elasticities are very high, averaging 0.64 for short run and 1.03 for long run. It should be pointed out that this major study estimated rail own elasticities to GVA, employment, car ownership, fare, journey time and late arrival time and none were deemed sufficiently reliable to be adopted in official forecasting practice in Great Britain.[18]

The multiplier in Study 12 (Blanchard, 2009), which is a published undergraduate thesis, implies very low cross-elasticities. All observations related to cross-elasticities of the demand for public transport modes with respect to fuel price in numerous United States cities. These may be seen to be atypical, with users generally captive to their chosen mode and cross-elasticities lower than might be expected on the basis of relative market shares.

The study-specific multiplier in Study 26 (Douglas et al., 2003) seems to stem from essentially zero cross-elasticities between public transport modes and car for almost half the observations whilst the cross-elasticities involving rail and bus were less than 0.15. We note here the use of a joint RP-SP approach and Brisbane might not be regarded as an ideal context for RP data or indeed the derivation of cross-elasticities given the dominance of car.

Study 65 relates to the Danish national model (Rich and Hansen, 2016). Whilst this was based on RP data, 9 of the 36 observations in our data set had cross-elasticities related to car as an alternative that all exceeded 0.6, split equally over public transport as a generic mode, walk and cycle, with mean values respectively of 0.91, 0.76 and 0.73.

Study 66 (Rich and Mabit, 2011) is a four-stage transport model that covers European wide trips Given that the pan-European databases that underpin such models are less reliable than their national or study-bespoke equivalents, we might expect the results to be less reliable.

The low multiplier for Study 86 (Wardman et al., 1997) seems to be attributable to eight low cross-elasticities for car as the affected mode which averaged 0.05 for inter-urban trips.

It would seem that the study-specific effects have discerned unaccounted for factors which on balance should not be allowed to impact on cross-elasticities forecast by the meta-model. The illustrative forecasts in section 5 do not therefore include the study-specific effects, although as already pointed out the net effect on the constant would be negligible.

---

[18] Ironically, this study's car cost cross-elasticities were adopted in version 5 of the Great Britain railway industry's Passenger Demand Forecasting Handbook in 2013, although they were dropped from the subsequent version 6 released in 2018.

Quality Issues

We here explore quality issues in a little more detail, over and above the study specific effects that have been isolated, given that a criticism levelled at meta-analysis is that it does not control for inevitable differences in the quality of the data assembled. For a number of reasons, we believe that the results of our meta-model are robust to issues of data and analysis quality.

Firstly, when the 5% of 'outlier' observations where the standardised residual lies outside the range ±1.96, which can be taken to represent the poorest quality observations, and even though this increased the adjusted R^2 appreciably to 0.741, it made very little difference to the coefficient estimates with a mean (absolute) deviation relative to the initial estimates of -0.02 (0.13).

Secondly, inspection of the outlier observations did not indicate any obvious quality related issues or indeed potential omitted variables over and above the insights from the study-specific effects[19].

Thirdly, it can be argued that quality issues will have a random effect on the estimated cross-elasticities. Why should poor quality evidence produce systematically lower or higher cross-elasticities? If quality is a random effect, it would in large samples as here be contained within the error term and not bias our coefficient estimates even in the absence of study specific effects.

Fourthly, some observers would argue that the best quality evidence is that reported in papers published in peer-reviewed academic journals. No significant difference between cross-elasticities sourced from journal articles and other means of dissemination was detected.

Finally, whilst the precision of cross-elasticity estimates could be taken as a measure of quality, and more emphasis placed upon more precise estimates, few studies report variances of the cross-elasticity estimates. Sample size might then be suggested as a proxy for precision but this is either meaningless, as with deduced or four-stage model cross-elasticities, or not directly comparable, as between regression and choice models. We have though explored and allowed for heteroscedasticity and found it to have a minor effect.

5. ILLUSTRATIVE IMPLIED CROSS-ELASTICITIES AND DEMAND FORECASTS

The estimated meta-model is here used to provide illustrative 'forecasts' of price (fuel or fare) and IVT cross-elasticities for a range of circumstances[20]. These are set out in Table 8 and relate to the main modes of car, bus and rail, primarily for a variety of urban trip features but with extension to inter-urban trips, and for the three main journey purposes.

[19] Recall that the study-specific effects do not cover the 16 (17%) studies where there is only one cross-elasticity observation and hence the residual would serve the purpose of identifying a 'rogue' observation.

[20] Of course, implied cross-elasticities can be calculated for other attributes in our meta-model but we restrict our discussion here to the most important.

A key factor in using our meta-model to provide cross-elasticity estimates is the relative demand of different modes. We here use summary figures from our data set, and for urban trips have selected the approximate 25th, 50th and 75th percentiles for each of V_C/V_B, V_R/V_B and V_C/V_R. These figures are 4, 7 and 14 for V_C/V_B, 0.4, 0.9 and 1.2 for V_R/V_B and 3, 10 and 16 for V_C/V_R[21]. Of course, a more extreme set of values could be used, such as a very high ratio of V_R/V_B and a very low ratio of V_C/V_R for commuting trips into major metropolis. Forecasts are also provided for inter-urban trips but only for the mean ratios in our dataset which are 21 for V_C/V_B, 5 for V_R/V_B and 4 for V_C/V_R.

The illustrative cross-elasticities are generally long run, based on the explicitly long run coefficient (*REGRESSION_LR*) and denoted LR in Table 8. Short run (SR) variants are also provided and these are based on the base estimation method in Table 6. The final feature is that the cross-elasticity forecasts are provided for the most recent year in the data set of 2017 but, given previous discussions regarding the time trends, a set of figures for the midpoint year of 2000 is also provided.

We are interested in forecasting CE of equation 2 but our estimated meta-model is a logarithmic transformation of it. If we simply take the exponential of the predicted value of our estimated model, we will introduce a source of bias. This is because if the error term in our estimated model follows a normal distribution, then the cross-elasticity will follow a log-normal distribution and its mean value will include the variance of the error term. Ignoring this latter term, which must be positive, would lead to forecasts that are under-estimates. The degree of error is an empirical issue. A general procedure for correcting for the error (Wooldridge, 2013), which is not dependent upon the errors being normally distributed, is to regress the actual cross-elasticities on the exponentiated cross-elasticities predicted by the meta-model and to suppress the intercept. The resulting slope coefficient is used to scale the 'naïve' cross-elasticity forecasts implied by our estimated meta-model. Given that the estimated slope coefficient was 1.06 (t=38.8), the adjustment would make little difference here and therefore we have not applied it.

The illustrative cross-elasticities exhibit an appreciable amount of variation, which is not only to be expected given the results of our meta-model but is in line with expectations surrounding cross-elasticities. The market share effect is clearly apparent for urban trips, and particularly drives the inter-urban cross-elasticities where market shares are somewhat different, whilst the cross-elasticities for IVT generally exceed those for price and the long run are noticeably larger than their short run counterparts. The cross-elasticities relating to car demand are generally low, especially so for urban trips, indicating that improvements to the cost and journey time of public transport modes might not be an efficient means of reducing the dependence upon car.

The pattern of implied cross-elasticities appears to be sensible. The variation is large enough to be in line with expectations but without implying extreme cross-elasticities that would cast doubts upon the estimated meta-model; there is no guarantee of such desirable properties!

---

[21] Given these summary ratios are obtained from different sets of cross-elasticity evidence, it would be most unlikely that they are 'internally consistent' in the sense of $(V_C/V_B) / (V_R/V_B) = V_C/V_R$. They are purely illustrative and other figures could have been used.

Table 8: Illustrative Forecast Cross-Elasticities

				Price						IVT					
	V_c/V_B	V_R/V_B	V_C/V_R	Bus:Car	Bus:Rail	Rail:Car	Rail:Bus	Car:Bus	Car:Rail	Bus:Car	Bus:Rail	Rail:Car	Rail:Bus	Car:Bus	Car:Rail
Commuting Urban LR 2017	4	0.4	3	0.16	0.17	0.21	0.34	0.06	0.07	0.33	0.18	0.42	0.38	0.07	0.08
Leisure Urban LR 2017	4	0.4	3	0.16	0.17	0.21	0.34	0.06	0.07	0.48	0.26	0.61	0.54	0.10	0.11
Business Urban LR 2017	4	0.4	3	0.11	0.11	0.13	0.22	0.04	0.05	0.45	0.25	0.57	0.51	0.10	0.11
Commuting Urban LR 2017	7	0.9	10	0.20	0.22	0.32	0.26	0.05	0.05	0.41	0.24	0.65	0.28	0.06	0.05
Leisure Urban LR 2017	7	0.9	10	0.20	0.22	0.32	0.26	0.05	0.05	0.58	0.35	0.93	0.40	0.08	0.07
Business Urban LR 2017	7	0.9	10	0.13	0.15	0.21	0.17	0.03	0.03	0.55	0.33	0.87	0.38	0.08	0.07
Commuting Urban LR 2017	14	1.2	16	0.25	0.25	0.37	0.23	0.04	0.04	0.52	0.27	0.77	0.26	0.05	0.04
Leisure Urban LR 2017	14	1.2	16	0.25	0.25	0.37	0.23	0.04	0.04	0.75	0.39	1.10	0.37	0.07	0.06
Business Urban LR 2017	14	1.2	16	0.17	0.16	0.24	0.15	0.03	0.03	0.70	0.36	1.03	0.34	0.06	0.06
Commuting Urban LR 2000	7	0.9	10	0.26	0.29	0.41	0.33	0.07	0.06	0.55	0.33	0.88	0.38	0.08	0.07
Leisure Urban LR 2000	7	0.9	10	0.26	0.29	0.41	0.33	0.07	0.06	0.79	0.47	1.26	0.55	0.11	0.10
Business Urban LR 2000	7	0.9	10	0.17	0.19	0.27	0.22	0.04	0.04	0.75	0.44	1.19	0.52	0.11	0.09
Commuting Inter LR 2017	21	5	4	0.29	0.71	0.49	0.14	0.04	0.18	0.60	0.78	1.02	0.15	0.04	0.20
Leisure Inter LR 2017	21	5	4	0.29	0.71	0.49	0.14	0.04	0.18	0.86	1.12	1.46	0.22	0.06	0.29
Business Inter LR 2017	21	5	4	0.19	0.47	0.32	0.09	0.02	0.12	0.81	1.05	1.37	0.21	0.05	0.27
Commuting Urban SR 2017	7	0.9	10	0.08	0.09	0.13	0.11	0.02	0.02	0.17	0.10	0.28	0.12	0.02	0.02
Leisure Urban SR 2017	7	0.9	10	0.08	0.09	0.13	0.11	0.02	0.02	0.25	0.15	0.40	0.17	0.04	0.03
Business Urban SR 2017	7	0.9	10	0.05	0.06	0.09	0.07	0.01	0.01	0.23	0.14	0.37	0.16	0.03	0.03

Note: The cross-elasticity headings denote mode affected:mode altered. The within-row demand ratios are simply combined as the set of lowest through to the set of highest given that there is no required consistency between them. The study-specific effects estimated are not used in producing these implied cross-elasticities.

Whilst it is not the purpose of this paper to evaluate policy measures that impact on the competitive situation between different modes, but rather to provide the means by which this might be done, we here provide some illustrative demand forecasts based on some implied cross-elasticities.

The results indicate that 'carrot incentives' can be expected to be minor in terms of reducing car demand. Let us take the commuting market with 'typical' V_C/V_B of 7 and V_C/V_R of 10. A 25% reduction in bus times, due to say bus priority measures, or a 25% reduction in bus fares, due to increased subsidy, would reduce car demand by only around 1.5% in the long run. The same would apply for equivalent improvements to trains. Indeed, if reductions in car demand in this market segment of just 10% were required, the required reduction in one of these variables would need to exceed 85%[22]. In major urban contexts where public transport performs better than these demand ratios would imply, yet where there is a greater need to reduce car use, the demand switching would be larger but not majorly so.

As for 'stick disincentives' to reducing car use, suppose a congestion charge was introduced that increased peak period car costs by 33%, which is certainly within the bounds of realism. It would be forecast to increase rail and bus demand by modest amounts of around 10% and 6% respectively. However, it would take only around half this level of increase in car in-vehicle time to achieve the same transfer to the public transport modes. Nonetheless, these forecast demand switches would be lower in the urban contexts where congestion pricing might be introduced which is where public transport shares are larger.

6. CONCLUDING REMARKS

Cross-elasticities are becoming increasingly important to policy makers and forecasters given greater interest in multi-modal transport planning in general and more specifically the challenges of limiting travel by less sustainable means.

There have though been few published reviews of cross-elasticity evidence, in contrast to own-elasticities, and most are now dated. We here report what is, as far as we are aware, by far the most extensive review and meta-analysis of cross-elasticity evidence.

When we embarked upon this study, we feared that we might uncover little evidence and would struggle to discern significant explanators of cross-elasticities particularly given that they are inherently variable. What has though emerged is a robust meta-model whose parameters are stable across different formulations with a sample size and goodness of fit that compare favourably with other transport meta-analysis studies covering own-elasticities and valuations which might be regarded to be inherently easier to explain. Indeed, our preferred model contains 37 parameters over and above the 20 study-specific effects, and over 80% of the estimated coefficients are significant at the 0.1% level with all others significant at least at the conventional 5% level.

[22] Although of course the cross-elasticities might be expected to be larger in such circumstances!

The large number of influences on cross-elasticities discerned by the meta-model are mostly in line with expectations. These covered attribute, the modes affected and altered, the estimation method, journey purpose, distance, time trend and relative market share. Notable findings are that:

- The meta-model can produce cross-elasticity forecasts for 12 attributes[23] and 35 combinations of mode affected and mode altered.
- Cross-elasticities do vary by estimation method, with long run elasticities exceeding those where no explicit account is taken of dynamic response, and there are concerns raised about cross-elasticities from SP choice models which exceed by some margin those having a basis in actual behaviour. These findings are consistent with evidence from other meta-analysis studies.
- The meta-model's estimated cross-elasticities do, as would be hoped, depend upon the relative demand of relevant modes, with the precise combination of mode affected and mode altered providing an additional influence.
- There is some variation by journey purpose.
- Cross-elasticities for car demand are relatively low, given its dominant position, and there is evidence to support larger cross-elasticities for inter-urban trips which are less routinely made.
- Cross-elasticities to time-based attributes tend to exceed those for price-based attributes.
- There is evidence that cross-elasticities have been falling over time.

The reported meta-model can be used to provide cross-elasticity estimates where none exist or to serve as benchmarks against which to evaluate emerging evidence. We have provided illustrative cross-elasticities, dependent upon attribute, mode, journey purpose, estimation method, year and whether a journey is urban or inter-urban, and these seem plausible across a wide range of different circumstances.

Acknowledgements

The research reported in this paper was financed by the Research Council of Norway as part of the 'Crossmodal' project (grant number 246836). We have benefitted from fruitful discussions and advice from Maria Börjesson of the Centre for Transport Studies at KTH Stockholm, Graham Currie of Monash University and Joyce Dargay.

References

Acutt, M. Z. and Dodgson, J. S. (1996). Cross-elasticities of Demand for Travel. Transport Policy, 2(4), pp.271-277.

[23] We would exclude the extreme forecasts for parking search time.

ARUP and OXERA (2010) Revisiting the Elasticity Based Framework. Report to Department for Transport.

Blanchard, C. (2009) The Impact of Rising Gasoline Prices on US Public Transit Ridership. Duke University, Durham, North Carolina. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.519.9406&rep=rep1&type=pdf

Bristow, A.L., Wardman, M. and Chintakayala, V.P.K. (2015) International Meta-Analysis of Stated Preference Studies of Transportation Noise Nuisance. *Transportation*, 42(1), pp. 71-100.

Brons, M., Pels, E., Nijkamp, P. and Rietveld, P. (2002) Price Elasticities of Demand for Passenger Air Travel: A Meta-Analysis. Journal of Air Transport Management, 8, pp.165-175.

Button, K.J. (1995) What can Meta-Analysis Tell Us About the Implications of Transport. *Regional Studies* 29, pp. 507-517.

Button, K.J. (2018) The Value and Challenges of Using Meta-Analysis in Transportation Economics. *Transport Reviews*.

Dargay, J.M., Clark, S., Johnson, D., Toner, J.P. and Wardman, M. (2010) A Forecasting Model for Long Distance Travel in Great Britain, Paper presented at 12th World Conference on Transport Research, Lisbon, July 11-15 2010.

De Jong, G. and Gunn, H.F. (2001): 'Recent Evidence on Car Cost and Time Elasticities of Travel Demand in Europe'. *Journal of Transport Economics and Policy,* 35 (2), 137-160.

Dodgson, J. S. (1986). Benefits of Changes in Urban Public Transport Subsidies in the Major Australian Cities. *Economic Record*, 62(2), 224-235.

Douglas, N.J., Franzmann, L.J., Frost, T.W. (2003) The Estimation of Demand Parameters for Primary Public Transport Service in Brisbane. Paper at the 26th Australasian Transport Research Forum Wellington, New Zealand 1-3 October 2003.

Espey, M. (1998) Gasoline Demand Revisited: An International Meta-Analysis of Elasticity. Energy Economics 20, pp.273-295.

Elvik, R. (2018) Meta-analytic Methods. Chapter 19 in Lord, D. and Washington, S. (eds): Safe Mobility, Challenges, Methodology and Solutions, Transport and Sustainability, Volume 11, pp. 423–445. Emerald Publishing, Bingley, UK.

Fearnley, N., Flügel, S., Killi, M., Gregersen, F.A., Wardman, M., Caspersen, E., Toner, J.P. (2017) Triggers of Urban Passenger Mode Shift – State of the Art and Model Evidence, *Transportation Research Procedia*, Vol 26, 2017, pp 62-80, https://doi.org/10.1016/j.trpro.2017.07.009

Fearnley, N., Currie, G., Flügel, S., Gregersen, F.A., Killi, M., Toner, J.P. and Wardman, M. (2018) Competition and Substitution between Public Transport Modes. Research in Transportation Economics, https://doi.org/10.1016/j.retrec.2018.05.005

Goodwin, P. (1992) A Review of New Demand Elasticities with Special Reference to Short and Long Run Effects of Price Changes, *Journal of Transport Economics and Policy,* 26 (2), 155-163

Goodwin, P, Dargay, J. and Hanly, M. (2004) Elasticities of Road Traffic and Fuel Consumption with respect to Price and Income: A Review. *Transport Reviews,* 24 (3), 275-292.

Graham, D.J. and Glaister, S. (2004) A Review of Road Traffic Demand Elasticity Estimates, *Transport Reviews*, 24 (3), 261-274

Gujarati, D.N. (2009) Basic Econometrics. Tata McGraw-Hill Education, New York.

Hensher, D.A. (2008): 'Assessing Systematic Sources of Variation in Public Transport Elasticities: Some Comparative Warnings', *Transportation Research A,* 42 (7), 1031-1042.

Holmgren, J. (2007) Meta-Analysis of Public Transport Demand. *Transportation Research A*, 41 (6), pp. 1021-1035.

Jevons, D., Meaney, A., Robins, N., Dargay, J., Preston, J., Goodwin, P. and Wardman, M. (2005) How do Rail Passengers Respond to Change? *Paper presented at AET European Transport Conference*

Kremers, H., Nijkamp, P. and Rietveld, P. (2002) A Meta-Analysis of Price Elasticities of Transport Demand in a General Equilibrium Framework. *Economic Modelling* 19, pp. 463-485.

Litman, T. (2010): 'Transportation Elasticities: How Prices and Other Factors Affect Travel Behaviour', Victoria Transport Policy Institute, Victoria, British Columbia, Canada. www.vtpi.org/elasticities.pdf.

Melo, P.C., Graham, D.J. and Brage-Ardao, R. (2013) The Productivity of Transport Infrastructure Investment: A Meta-Analysis of Empirical Evidence. Regional Science and Urban Economics, 43 (5), pp.695-706.

O'Brien, R. M. (2007) A Caution Regarding Rules of Thumb for Variance Inflation Factors. Quality and Quantity, vol 41 (5): 673. doi:10.1007/s11135-006-9018-6.

Oum, T.H., Waters, W.G., Jr., Yong, J.S. (1992): 'Concepts of Price Elasticities of Transport Demand and Recent Empirical Estimates', *Journal of Transport Economics and Policy*, 26 (2), 139-154.

Rich, J. and Mabit, S.L. (2011) A Long-Distance Travel Demand Model for Europe. European Journal of Transport and Infrastructure Research, Vol. 12, No. 1, pp. 1-20

Rich, J. and Hansen, C.O. (2016) The Danish National Passenger Model: Model Specification and Results. European Journal of Transport and Infrastructure Research, 16 (4), pp. 573-599.

Transportation Research Board (2004): 'Travel Response to Transportation System Changes: Chapter 12 – Transit Pricing and Fares'. Transit Cooperation Research Program Report 95, Washington DC.

Transport Research Laboratory, Centre for Transport Studies University College London, Transport Studies Unit University of Oxford, Institute for Transport Studies University of Leeds, Transport Studies

Group University of Westminster (2004): 'Demand for Public Transport: A Practical Guide'. TRL Report TRL593, Crowthorne, Berkshire.

Wallis, I. (2004) Review of Passenger Transport Demand Elasticities. Transfund New Zealand Research Report No 248. Wellington, New Zealand.

Wardman, M. (2014) Price Elasticities of Surface Travel Demand: A Meta-analysis of UK Evidence. *Journal of Transport Economics and Policy*, 48 (3), pp. 367 – 384.

Wardman, M. (2012) Review and Meta-Analysis of U.K. Time Elasticities of Travel Demand. *Transportation* 39 pp.465-490.

Wardman, M. (1997a) Disaggregate Inter-Urban Mode Choice Models: Review of British Evidence with Special Reference to Cross Elasticities, Working Paper 504, Institute for Transport Studies, University of Leeds.

Wardman, M. (1997b) Disaggregate Urban Mode Choice Models: Review of British Evidence with Special Reference to Cross Elasticities, Working Paper 505, Institute for Transport Studies, University of Leeds.

Wardman, M., Toner, J.P and Whelan, G.A. (1997) Interactions between Rail and Car in the Inter Urban Leisure Travel Market in Great Britain. *Journal of Transport Economics and Policy, 31*(2), 163-181*.*

Wardman, M., Chintakayala, V.P.K. and de Jong, G. (2016) Value of Travel Time in Europe : Review and Meta-Analysis. *Transportation Research A*, 94, pp.93-111.

Webster, V. and Bly, P. (1980) The Demand for Public Transport*,* Transport and Road Research Laboratory, Crowthorne, Berkshire.

White, H., 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. Econometrica 48, pp.817-838.

Wooldridge, J.M. (2013*)* Introductory Econometrics: A Modern Approach*.* Fifth Edition. South-Western, Mason, Ohio, USA.

APPENDIX: OTHER CANDIDATE META-MODELS

		II		III	IV	
		Standard Multiplicative Model Direct Estimation		Additive Model	Random Effects Multiplicative Log Transform	
		Coeff (t)	Effect	Coeff (t)	Coeff (t)	Effect
	CONSTANT	-2.516 (11.3)		-0.014 (0.4)	-3.249 (11.0)	
Attribute Base = fuel	FARE	0.348(2.4)	*1.42	0.226 (6.6)	0.672 (5.0)	*1.96
	IVT	0.669 (3.7)	*1.95	0.162 (5.0)	0.823 (6.2)	*2.28
	ACCEGR_TRANSFER	0.203 (0.6)	*1.23	0.052 (2.2)	0.644 (3.3)	*1.91
	JT	0.877 (3.5)	*2.40	0.078 (2.1)	0.647 (3.2)	*1.91
	PARKTIME	2.784 (2.5)	*16.18	0.939 (5.1)	2.530 (3.3)	*12.56
	RESTCOST	-0.888 (1.9)	*0.41	-0.143 (3.8)	-1.176 (4.8)	*0.31
Modal Combinations including distance interactions Base = Car_Bus	BUS_RAIL	0.895 (3.6)	*2.45	0.053 (1.6)	0.806 (4.2)	*2.24
	BUS_LRTMETRO	0.738 (1.6)	*2.09	0.069 (1.5)	1.280 (3.8)	*3.60
	BUS_AIR	-3.804 (0.2)	*0.02	-0.153 (3.3)	-2.539 (7.9)	*0.08
	BUS_CAR	0.799 (4.9)	*2.22	0.147 (4.5)	0.529 (3.4)	*1.70
	LRT_CAR	0.860 (1.7)	*2.36	0.196 (3.3)	1.077 (3.4)	*2.94
	LRTMETRO_BUS	0.586 (1.3)	*1.80	0.018 (0.6)	0.837 (2.6)	*2.31
	RAIL_CAR	1.098 (6.5)	*3.00	0.234 (6.6)	0.647 (3.8)	*1.91
	RAIL_BUS	0.502 (2.5)	*1.65	0.050 (2.2)	0.818 (5.6)	*2.27
	RAIL_AIR	0.260 (0.5)	*1.30	0.099 (1.4)	1.359 (4.3)	*3.89
	AIR_BUS	-3.290 (0.2)	*0.04	-0.179 (5.4)	-2.735 (8.5)	*0.06
	AIR_RAIL	0.936 (4.6)	*2.55	0.183 (3.2)	1.153 (4.7)	*3.17
	WALK_BUSRAILPTLRT	-1.455 (0.9)	*0.23	-0.082 (2.8)	-1.000 (4.5)	*0.37
	CYCLE_RAIL	-0.813 (0.3)	*0.44	-0.061 (2.1)	-1.108 (2.7)	*0.33
	PT_CAR	1.003 (6.8)	*2.73	0.268 (7.0)	0.688 (4.0)	*1.99
	BUS_RAIL_INTER	0.215 (0.9)	*1.24	0.166 (3.1)	0.447 (1.7)	*1.56
	CAR_RAIL_INTER	0.393 (1.5)	*1.48	0.040 (1.7)	0.945 (5.2)	*2.57
	RAIL_CAR_INTER	0.225 (1.9)	*1.25	0.143 (4.0)	0.893 (5.8)	*2.44

Estimation Method Base = Deduction	REGRESSION_CROSS	0.670 (2.9)	*1.95	0.274 (2.6)	1.552 (3.4)	*4.72
	REGRESSION_LR	0.624 (5.2)	1.87	0.199 (4.6)	0.868 (4.6)	*2.38
	REGRESSION_ND	0.235 (1.9)	*1.26	0.046 (2.0)	0.365 (2.3)	*1.44
	FOURSTAGE	0.508 (4.2)	*1.66	0.140 (4.4)	0.350 (0.9)	*1.42
	CHOICE_SP	0.799 (5.9)	*2.22	0.219 (5.9)	1.106 (4.9)	*3.02
	OBSERVED	0.900 (3.3)	*2.46	0.225 (3.0)	1.203 (2.9)	*3.33
Journey Purpose including Interactions with Distance and Attribute Base = Leisure	BUSINESS	0.337 (3.3)	*1.40	0.081 (1.4)	-0.489 (3.6)	*0.61
	BUSINESS_LONG	-1.260 (1.8)	*0.28	-0.255 (3.5)	-0.997 (3.4)	*0.37
	BUSINESS_TIME	0.254 (2.1)	*1.29	0.196 (2.2)	0.733 (3.6)	*2.08
	LEISURE_TIME	0.277 (3.7)	*1.32	0.105 (2.9)	0.312 (2.4)	*1.37
Distance Base = Urban	LONG	-0.667 (3.4)	*0.51	-0.245 (5.8)	-0.369 (1.2)	*0.69
Relative Demand	DEMAND_RATIO	0.127 (6.1)		0.048 (8.8)	0.372 (15.6)	
Time Trend	TREND_TIME	-0.008 (1.5)	*0.99	0.001 (1.3)	-0.010 (1.3)	*0.99
	TREND_PRICE	-0.009 (2.0)	*0.99	-0.002 (4.1)	-0.012 (1.6)	*0.99
Study Specific Effects	Study1 (12)	-1.391 (0.8)	*0.25	-0.085 (2.7)		
	Study2 (5)	-1.407 (0.5)	*0.24	-0.082 (2.0)		
	Study3 (6)	0.540 (0.6)	*1.72	0.040 (1.0)		
	Study6 (10)	0.722 (5.1)	*2.06	0.419 (3.3)		
	Study12 (34)	-1.284 (2.1)	*0.28	-0.169 (5.9)		
	Study17 (5)	-1.430 (1.2)	*0.24	-0.295 (6.6)		
	Study18 (4)	-0.771 (0.7)	*0.46	-0.146 (2.8)		
	Study24 (14)	-2.032 (0.2)	*0.13	0.046 (1.8)		
	Study25 (2)	1.043 (1.2)	*2.84	0.226 (1.4)		
	Study26 (48)	-0.447 (2.0)	*0.64	-0.077 (2.8)		
	Study51 (5)	-1.029 (1.1)	*0.36	-0.287 (7.4)		
	Study55 (2)	2.173 (6.4)	*8.79	0.771 (2.0)		
	Study58 (3)	0.671 (0.8)	*1.96	0.127 (2.2)		
	Study63 (8)	-1.240 (1.1)	*0.29	-0.130 (1.7)		
	Study65(36)	0.535 (3.2)	*1.71	0.038 (1.0)		
	Study66 (22)	-0.061 (0.1)	*0.94	0.134 (2.9)		
	Study74 (7)	-1.519 (1.1)	*0.22	-0.266 (5.1)		
	Study78 (8)	-1.310 (1.5)	*0.27	-0.262 (5.6)		

	Study86 (12)	-0.282 (1.0)	*0.75	-0.166 (4.3)	
	Study93 (7)	0.523 (2.0)	*1.69	0.132 (3.0)	
	RSS	61.75		69.72	1289.14
	ESS	64.45		56.48	1494.58
	Adj R^2	0.483		0.417	0.521

Note: Model Types are as defined in Section 4.2. DEMAND_RATIO is entered in logarithmic form in Models II and IV.