DEAKIN
UNIVERSITY AUSTRALIA

Faculty of Business and Law
School of Accounting, Economics and Finance

School Working Paper

ECONOMICS SERIES

SWP 2014/6

THE INCOME ELASTICITY OF AIR TRAVEL:

A META-ANALYSIS

Craig Gallet and Hristos Doucouliagos

THE INCOME ELASTICITY OF AIR TRAVEL: A META-ANALYSIS

By

Craig A. Gallet*
Department of Economics
California State University, Sacramento

And

Hristos Doucouliagos
School of Accounting, Economics and Finance
Deakin University

August 2014

Abstract:

There is much disparity in estimates of the income elasticity of air travel across the literature. We examine this disparity by applying meta-regression techniques. Controlling for several issues, including publication selection bias, while our preferred baseline income elasticity estimate of 1.186 is consistent with air travel being a luxury and a slightly immature market, there are several features of the literature which sway the income elasticity away from this baseline. For instance, the income elasticity increases to 1.546 on international routes, yet decreases to 0.633 when air fare is included in a dynamic specification of demand, *ceteris paribus*. Other characteristics of the literature, such as those involving various data and estimation choices, have less influence on the reported income elasticity.

Keywords: income elasticity, air travel, meta-regression analysis

* Corresponding author: Craig A. Gallet; Department of Economics; California State University, Sacramento; 6000 J Street; Sacramento, CA 95819-6082; E-mail: cgallet@csus.edu; Phone: 916-278-6099; Fax: 916-278-5768.

INTRODUCTION

Many studies have estimated the demand for air travel, reporting a multitude of elasticity estimates. While literature reviews (Oum, Waters, & Yong, 1992; Brons, Pels, Nijkamp, & Rietveld, 2002; Kremers, Nijkamp, & Rietveld, 2002) have surveyed estimates of the price elasticity of air travel (defined as the ratio of the percentage change in demand for air travel to the percentage change in air fare), no study has systematically reviewed estimates of the income elasticity of air travel (defined as the ratio of the percentage change in demand for air travel to the percentage change in consumer income).

Knowledge of the income elasticity of air travel is useful for a number of reasons. First, the income elasticity is important in terms of forecasting air travel. For instance, a higher positive value of the income elasticity implies a greater response of air travel to changes in income, thus placing greater (lesser) pressure on air transport systems during periods of rising (falling) income. Second, the magnitude of the income elasticity provides information on how consumers view air travel, be it a luxury (i.e., income elasticity exceeds 1) or a necessity (i.e. income elasticity lies between 0 and 1). With such information available, if consumers view some routes (e.g., international travel) as luxuries, yet others (e.g., domestic travel) as necessities, airlines can better target promotion strategies to different market segments. Third, several studies (Graham, 2000; Graham, 2006; Department of Transport, 2013) rely on the income elasticity to classify air transport market maturity. For instance, Graham (2000) defines an immature market as having an income elasticity exceeding 1 (i.e., growth potential is higher), a fully mature market as having an income elasticity at or below 1 (i.e., growth potential is lower), and a fully saturated market as having an income elasticity of 0 (i.e., no growth potential).

Hence, knowledge of the income elasticity can shed light on market maturity, which can facilitate decision-making in regards to exploring investment opportunities in higher-growth markets. Fourth, air transportation management and regulators rely on pricing to reduce congestion and pollution. However, the effectiveness of pricing policies depends on the income elasticity of air travel, for rising incomes may offset the influence of price on air travel. Accordingly, knowledge of the income elasticity is important when evaluating the efficacy of such policies. Fifth, understanding what drives income elasticity estimates in the literature can suggest avenues for future research.

In light of these reasons, similar to meta-analyses of the income elasticities of tourism (Crouch, 1992), water (Dalhuisen, Florax, & de Groot, 2003), cigarettes (Gallet & List, 2003), money (Knell & Stix, 2005), and meat (Gallet, 2010), this paper utilizes meta-regression analysis (MRA) to quantitatively survey the literature on the income elasticity of air travel. Specifically, unlike traditional qualitative literature reviews, which can suffer from the subjective decisions of the reviewer to attach too little or too much importance to particular elasticity estimates, we apply statistical techniques to assess the impact of various features of the literature on the income elasticity. By doing so, statistical tests are used to address several issues, such as sampling error, mis-specification, and publication selection biases, in order to arrive at underlying estimates of the income elasticity.

Briefly, we find several attributes of the literature significantly impact estimates of the income elasticity of air travel. For instance, once we control for other study characteristics, our results show that the income elasticity has historically been largely insensitive to location, as the literature has found it to be similar across Asia, Australia and New Zealand, Europe, and North

America (principally the United States). Yet the income elasticity for international flights does tend to be higher than domestic flights. Also, the chosen econometric specification of air travel demand, most noticeably the choice of independent variables and the functional form of demand, influences the reported income elasticity. However, a number of other features (e.g., those involving data aggregation and estimation method) have less influence on the income elasticity. In the sections that follow, the meta-regression model is presented, followed by the estimation results, while the paper concludes with a summary of the findings.

META-REGRESSION MODEL

Our data collection and meta-regression analysis followed the recently established MAER-NET guidelines (Stanley et al., 2013). Utilizing search engines (i.e., Econlit, Social Science Research Network (SSRN), and Google Scholar), as well as perusing studies that have reviewed literature related to tourism and air travel demand (i.e., Oum et al., 1992; Crouch, 1992; Crouch, 1994; Crouch, 1995; Lim, 1997; Lim, 1999; Brons et al., 2002; Kremers et al., 2002; Gillen, Morrison, & Stewart, 2007), we initially identified 51 studies that provide estimates of the income elasticity of air travel. Of these 51 studies, three assess the impact of income on island tourism (Garín-Muñoz, 2006; Garín-Muñoz & Montero-Martin, 2007; Nelson, Dickey, & Smith, 2011) using air passenger arrivals as the measure of tourism. Since this measure is similar to that used by studies of air travel demand, we chose to include these studies in the analysis.

In order to be included in the final meta-data set, a study had to report income elasticity estimates together with standard errors. Standard errors are essential for MRA in order to detect and correct for publication selection bias (see below). However, 11 of the 51 studies either did not provide sufficient information to obtain standard errors or reported outlier estimates of the income elasticity (discussed below). As a consequence, our meta-analysis is performed on the 40 studies listed in Table 1, which provided 405 estimates of the income elasticity. As Table 1 shows, while the mean income elasticity estimate for the majority of studies exceeds 1, suggesting air travel is a luxury and an immature market, 12 of the 40 studies report mean income elasticity estimates that are less than 1, which is consistent with air travel being a necessity and a fully mature market.

Please insert Table 1 about here

Meta-Regression Specification

In light of the variation in income elasticity estimates exhibited in Table 1, similar to other meta-analyses of the income elasticity (i.e., Crouch, 1992; Dalhuisen et al., 2003; Gallet & List, 2003; Knell & Stix, 2005; Gallet, 2010), a meta-regression model is estimated to address how sensitive the income elasticity of air travel is to study characteristics. Specifically, we estimate versions of the following:

$$E_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \bullet\bullet\bullet + \beta_K X_{Kij} + u_{ij}, \quad (1)$$

where E_{ij} denotes the i^{th} income elasticity estimate from the j^{th} study, X_{1ij} to X_{Kij} are independent variables relating to study characteristics, β_0 to β_K are coefficients to be estimated, and u_{ij} is an error term. Estimates from Equation 1 quantify how the income elasticity varies according to research design and data differences. In meta-analysis (particularly for medical research), many researchers adopt a 'random-effects' MRA model (Thomson & Sharp, 1999). However, Stanley and Doucouliagos (2012) caution against using random effects as the effects may not be independent of the MRA model's independent variables, and thus coefficient estimates will be biased, particularly in the face of publication selection. Instead, Stanley and Doucouliagos (2012) recommend estimating Equation 1 using unrestricted weighted least squares (WLS) instead of random effects.

The independent variables in Equation 1 account for key differences in the literature. For instance, similar to studies of the income elasticity of tourism (e.g., Crouch, 1992), one noticeable difference in the literature is demand location (i.e., origin of flight). In particular, while the majority of studies estimate income elasticities corresponding to flights originating in North America (principally the United States), a number of other studies address the demand for flights originating in Asia, Australia and New Zealand, Europe, and a few other locations (e.g., Israel from Alperovich and Machnes (1994)). Also, some studies focus on international flights, whereas others focus on domestic flights. Since recent industry forecasts (e.g., Rolls-Royce, 2012; Boeing, 2013) expect future demand growth to be higher (lower) in Asia (North America), especially on international (domestic) routes, the Asian (North American) markets currently being viewed as less (more) mature could signal regional differences in historical estimates of the income elasticity across the literature.

Studies also differ in a number of ways regarding the specification of air travel demand. First, while a few studies estimate a linear version of demand, the vast majority estimate a double-log version of demand, for which the income elasticity is the estimated coefficient of income. Second, most income elasticity estimates come from specifications of air travel demand that also control for the impact of price (i.e., air fare). Third, a static specification of demand (i.e., all variables in contemporaneous terms) is most commonly estimated in the literature, although several recent studies (e.g., Garín-Muñoz, 2006; Garín-Muñoz & Montero-Martin, 2007; Tsekeris, 2009; Chi & Baek, 2012) have estimated dynamic versions of demand by including lagged variables in the model. Accordingly, most income elasticity estimates correspond to the short-run (i.e., immediate response of demand to income changes) rather than the long-run (i.e., demand response to income changes over a longer period of time). Fourth, studies differ in terms of how income is measured. In particular, most studies measure "income" as income at the location where the flight originates (e.g., Garín-Muñoz & Montero-Martin, 2007), while some studies define "income" as the product of the incomes at the origin and destination locations (e.g., Verleger, 1972), the average of the incomes at the origin and destination locations (e.g., Ippolito, 1981), or the sum of the incomes at the origin and destination locations (e.g., Talley & Eckroade, 1984). Furthermore, a few studies (e.g., Vitek & Taneja, 1975; Mutti & Murai, 1977) use consumer expenditure as a proxy for income.

There are a few issues concerning data and estimation techniques that further contribute to differences in the literature. In particular, while earlier studies most often relied on time-series or cross-sectional data to estimate air travel demand, studies of late have increasingly relied on panel data to estimate demand (e.g., Garín-Muñoz & Montero-Martin, 2007; Tsekeris, 2009; Britto et al., 2012). Studies also differ in terms of data aggregation, with most income elasticity estimates coming from demand functions that are estimated using country-level data. Fewer income elasticity estimates are generated from data aggregated to the state-level, city-pair level (i.e., travel from one city to another city), or other levels (e.g., data at the individual consumer or airline levels). As for estimation, although the majority of studies rely on ordinary least squares (OLS) to estimate demand, and thus do not control for endogeneity of right-side variables (which typically involves price) in the specification of demand, other studies (e.g., Anderson & Kraus, 1981; Ippolito, 1981; Fleming & Ghobrial, 1994; Britto et al., 2012) use an instrumental variables procedure (such as two stage least squares) to control for endogeneity.

Finally, nearly one-half of the income elasticity estimates are from non-published studies (i.e., working papers), and thus have not gone through the vetting process associated with peer-reviewed publications. Also, studies which rely on earlier data may report income elasticities that differ from studies which rely on more recent data, perhaps because consumer preferences, data quality, or empirical methods beyond those mentioned change over time. Accordingly, we note the median year of the sample used to estimate each income elasticity estimate. With the exception of the median year of the sample, all other differences in the literature are qualitative in nature. Thus, common in meta-analysis, we use dummy variables to account for most of the independent variables in Equation 1, with each dummy variable set equal to 1 if a particular study characteristic holds and 0 if not. Variable definitions, along with means and standard deviations, are provided in Table 2.

Please insert Table 2 about here

Estimation Issues

There are several issues concerning the estimation of Equation 1. First, since a number of the categories in Table 2 encompass all observations of the income elasticity, several dummy variables must be dropped from Equation 1 to avoid perfect multicollinearity. In particular, we drop the dummy variables *North America*, *Domestic*, *Double-Log*, *Static*, *Short-run*, *Income Origin*, *Panel*, and *OtherAgg*, which then defines the "baseline" category. That is, setting all included variables in Equation 1 equal to zero defines the baseline income elasticity estimate as β_0, which amongst other factors, corresponds to a short-run income elasticity estimate of the static demand for air travel in North America.

Second, there are a few income elasticity estimates which were removed as outliers from the meta-data. Specifically, we commenced with 414 observations but subsequently removed nine observations, all of which had a meta-regression standardized residual greater than 3.5. Third, since we are using several estimates from each study, we cannot assume that the estimates reported within each study are statistically independent. Hence, we correct the standard errors for potential dependence by adjusting for the clustering of observations within studies (Stanley & Doucouliagos, 2012).

Fourth, although not addressed in earlier meta-analyses (e.g., Crouch, 1992; Gallet & List, 2003), publication selection bias is an issue that has garnered much attention in meta-analyses of late. Many authors have found that researchers select which findings to report. While this selection is usually dictated by journal space limitations, it can often also be motivated by a preference for certain results. This process has the potential to result in incorrect statistical inference (Stanley & Doucouliagos, 2012). For example, if there is a preference in favor of statistically significant results, then the reported elasticity might appear to be more important when it is not (in a statistical sense). Similarly, and more appropriately for our current study, given the mean income elasticity in Table 1 most often exceeds 1, if there is a preference in favor of reporting large income elasticities then the literature will give the impression that demand is more responsive to income than it is in reality. Thus, for instance, air transport decision-makers may perceive air travel as an immature market, when in reality it is not. This could lead to poor decision-making when it comes to investment decisions predicated on greater demand growth. Fortunately, techniques have been developed that both identify the presence of publication selection bias and correct its effects in the literature (Stanley, 2008; Stanley & Doucouliagos, 2012). By doing so, more accurate estimates of the income elasticity can be ascertained.

Consider Figure 1, which is a funnel plot of the income elasticity estimates. Specifically, the funnel plot illustrates the distribution of the reported estimates, with the precision of each estimate provided on the vertical axis. Precision is here measured as the inverse of the standard error of each income elasticity estimate and measures how reliable are the point income elasticity estimates (i.e., the greater the precision the more reliable is the estimate). A literature that is free of publication selection bias will have a symmetrical funnel. Although the average income elasticity in our sample is 1.517, with an associated 95% confidence interval (1.17 to 1.85) strongly suggesting that air travel is a luxury and a fairly immature market, it is clear from Figure 1 that there is much asymmetry in the data as (i) there is a noticeable absence of negative elasticities (although a reasonable expectation is that air travel is a normal good) and (ii) there are several large elasticity estimates with low precision. Such low precision estimates are assigned lower weight in the meta-analysis literature (see Stanley & Doucouliagos, 2012). Indeed, following the standard approach in meta-analysis, we calculated the weighted average income elasticity using precision as the weight, and the resulting value of 0.642 (with a 95% confidence interval of 0.31 to 0.97) now favors air travel being a necessity and a fully mature market.

Please insert Figure 1 about here

Furthermore, Table 3 reports the results of the FAT-PET test (or the Funnel Asymmetry Precision Effect Test), which is based on estimation of the following:

$E_{ij} = \beta_0 + \beta_{se}SE_{ij} + u_{ij}$,

(2)

where SE_{ij} denotes the standard error of the i^{th} income elasticity estimate from the j^{th} study and β_{se} is its corresponding coefficient (see Stanley, 2008). Equation 2 is a formal test for the presence of publication selection bias (which is a test of $\beta_{se} = 0$, known as the FAT) and an estimate of the income elasticity corrected for selection bias (which is the value of the test statistic corresponding to the test of $\beta_0 = 0$, known as the PET). In the absence of selection bias, there should be no relationship between the estimated income elasticity and its standard error, i.e. $\beta_{se} = 0$. In contrast, if there is selection bias, this is consistent with authors re-estimating their models until they come up with a 'desirable' result. The consequence of doing so is that the coefficient of the standard error in Equation 2 will be statistically significant. It can be seen from column 3 of Table 3 that the coefficient of the standard error is indeed statistically significant, with the large positive coefficient suggesting authors have a preference for reporting highly positive income elasticities. However, as we show below, once other dimensions of the research process are considered, publication selection bias is less of a concern in this literature.

Please insert Table 3 about here

Research (e.g., Stanley & Doucouliagos, 2012) has shown that it is often better to use a non-linear term to test for publication selection bias, and so we also estimated the PEESE (or Precision-Effect Estimate with Standard Error) model, which involves replacing the standard error in Equation 2 with its square. The results presented in column 4 of Table 3 also favor publication selection bias. In spite of the strong evidence of publication bias, both FAT-PET and PEESE estimate a positive income elasticity corrected for the effects of selection bias. The FAT-PET produces a point estimate of 0.47 (with a 95% confidence interval of 0.13 to 0.82), while PEESE estimates a larger effect, 0.70 (with a 95% confidence interval of 0.33 to 1.06). Thus, both are consistent with air travel being a necessity and a fully mature market, contrary to the majority of sample means reported in Table 1. Nonetheless, these results do need to be interpreted with caution as they do not consider heterogeneity in reported estimates, which is addressed by the meta-regression results in the next section.

META-REGRESSION RESULTS

Since we find evidence of publication selection bias, we estimate a modified version of Equation 1 by also including the standard error of the income elasticity as a regressor in the meta-regression. Several different versions of this modified meta-regression were then estimated, with the first set of estimations corresponding to the full specification of Equation 1 (i.e., all independent variables included). Specifically, initially we commenced with baseline OLS results. These are presented in column 1 of Table 4. The main limitation of this regression is that equal weight is assigned to all observations (elasticities). But as mentioned previously, in meta-analysis preference is given to assigning greater weight to estimates that are reported with greater precision. Estimates with greater precision are more representative of the underlying population income elasticities and hence should be assigned a higher weight. Accordingly, the other columns in Table 4 present results using WLS, with the inverse variance as weights, which are considered as 'optimal weights' in the literature (Hedges & Olkin, 1985). Columns 2 – 4 present results based on different standard error constructions, and thus the regression coefficient estimates are the same across these three columns. Specifically, column 2 presents the WLS results using robust standard errors, while column 3 presents results using cluster-adjusted standard errors (with clustering at the study level). Previous studies have shown that a small number of clusters can result in downward biased standard errors (Moulton, 1990; Cameron, Gelbach, & Miller, 2008). The number of clusters in our database is 40, which according to Angrist & Pischke (2008) is just sufficient to reliably cluster standard errors without downward bias in the standard errors. However, this is based on Monte Carlo simulations by Cameron et al. (2008) and others that assume equal sized clusters. In contrast, our clusters are very unequal (Table 1). MacKinnon and Webb (2013) suggest in the case of unequal clusters it is preferable to use the wild bootstrap procedure outlined in Cameron et al. (2008). These results are reported in column 4.

Please insert Table 4 about here

It is customary in MRA to apply a general-to-specific modeling strategy (see Stanley & Doucouliagos, 2012) since this results in greater clarity in the analysis of the underlying data generating process. We applied a general-to-specific approach using wild bootstrap standard errors and report these results in column 1 of Table 5. This is our preferred meta-regression model because it uses conservative standard errors to test Null hypotheses. We can see in Table 5 that some of the results from the general-to-specific approach differ from those reported in Table 4. In particular, the coefficients of *AustNZ* and *Europe* are statistically significant in columns 2 and 3 of Table 4, but they are no longer statistically significant in column 1 of Table 5 when more conservative standard errors are used to construct confidence intervals. Similarly, the coefficient of *IV* is statistically significant in columns 1 – 3 of Table 4 but not in column 1 of Table 5, whereas the coefficient of *City* is only statistically significant in Table 5. Yet there are also several similarities in the results across the various meta-regressions. For instance, the coefficients of several variables (i.e., *Asia*, *Income Product*, *Expenditure*, *Country*, and *Work*) are not only statistically insignificant in all columns of Table 4, but these variables are also dropped from the meta-regression when using the general-to-specific approach.

Please insert Table 5 about here

Across all meta-regressions, the constant term is interpreted as the income elasticity for the baseline after correcting for potential publication selection bias. Controlling for study characteristics, the baseline income elasticity slightly exceeds 1 in all meta-regressions, and is close to the simple average reported in Table 3. Accordingly, this implies that for the baseline region of North America air travel is a modest luxury and a slightly immature market. However, since this is the baseline income elasticity, which amongst other factors also corresponds to the short-run and domestic income elasticity, caution should be taken in comparing this to the average across the literature in general.

Regarding publication selection bias, the results are mixed, as the coefficient of the standard error being significantly (insignificantly) different from zero in columns 1 and 2 (3 and 4) of Table 4 does (does not) favor publication bias. Moreover, the preferred general-to-specific approach in column 1 of Table 5 removes the standard error variable from the meta-regression all together. Thus, while the basic tests in Table 3 favor the presence of publication selection bias, in general this is not supported once the various dimensions of the research are factored. This could be interpreted as a very encouraging result, given the fairly large degree of publication selection bias detected in economics and business research (Roberts & Stanley, 2005; Doucouliagos & Stanley, 2013). One explanation for this finding is that the income elasticity can theoretically take a wide range of values. Hence, there is no strong theoretical consensus in this literature that could potentially constrain reported estimates.

Turning attention to the preferred results in column 1 of Table 5, the model performs very well in terms of explaining heterogeneity in income elasticities, with 68% of the variation explained by the variables in column 1. The remaining variation can be attributed to sampling and random errors.

There are several interesting results in column 1 of Table 5 concerning individual study characteristics. First, of the four regional dummy variables, only the coefficient of *OtherLoc* is statistically significant. Holding other study characteristics constant, this implies the literature has found little difference in the income elasticity estimates of air travel across the regions of North America, Asia, Australia and New Zealand, and Europe. Interestingly, Crouch (1992) finds the income elasticity of tourism is also historically similar across some regions, notably North America and Europe. While it may be tempting to infer from such results that there is little regional difference in income elasticities (and thus market maturity) at any given point in time, which is contrary to recent industry forecasts (e.g., Rolls-Royce, 2012; Boeing, 2013), we caution drawing such an inference since it fails to acknowledge historical differences in the literature. In particular, our analysis being historical in nature assesses the income elasticity across markets and time. Accordingly, it may be that earlier studies tended to focus on markets (e.g., North America and Europe) which at the time were of a similar maturity to markets examined by more recent studies (e.g., Asia). Thus, although from a historical perspective the income elasticity estimates appear similar across regions, at any given point in time they may differ nonetheless.

Second, concerning the coefficient of *International* in column 1 of Table 5, it being statistically significant and with a value of 0.360 implies the income elasticity increases from 1.186 to 1.546 on international routes, *ceteris paribus*. This estimate is in the neighborhood of the income elasticity for international tourism (Crouch, 1992; Song, Kim, & Yang, 2009). Thus, compared to the baseline, studies have found air travel on international routes is not only more of a luxury, but markets for which a greater share of air travel is international are less mature and offer greater prospects for future growth.

Third, the income elasticity tends to be lower when the demand specification is linear and dynamic, air fare and average income are included in demand, and city-level panel data is used to estimate demand. Accordingly, compared to the baseline, if one is interested in the income elasticity of a flight between one city and another city, based on the results in column 1 of Table 5 the income elasticity drops from 1.186 to 0.605, which is in the range of a necessity and a very mature market. Also, finding that including air fare in demand affects the income elasticity is consistent with the presence of omitted variable bias when air fare is excluded from demand. Interestingly, in an MRA of the price elasticity of air travel, Brons et al. (2002) find the price elasticity of air travel is sensitive to whether or not income is included in the specification of demand. Accordingly, although one may consider excluding air fare and/or income from the estimation of air travel demand, perhaps due to lack of reliable data, the results in Table 5, as well as the findings of Brons et al. (2002), suggest both air fare and income should be included when estimating the demand for air travel.

Fourth, another important finding is that studies utilizing more recent data tend to report higher income elasticity estimates, *ceteris paribus*. However, the magnitude of the coefficient of *Year* in column 1 of Table 5 being so small implies the income elasticity is merely growing by a value of 0.05 per decade. Although this may appear contrary to studies predicting the income elasticity of air travel declines over time as markets mature, which has been found in particular markets (e.g., see Graham, 2000; Graham, 2006), since our historical analysis considers a multitude of studies that vary according to markets examined, empirical design, and data, it remains plausible that for any given market the income elasticity declines over time as the market matures. For instance, amongst other factors, it may simply be that greater availability of better data has afforded later studies the opportunity to explore previously neglected market segments, perhaps delineated by region (e.g., less developed versus more developed), route (e.g., domestic versus international), or consumers (e.g., business versus leisure travelers), all of which could contribute to changes in reported income elasticities over time.

Perusing the studies listed in Table 1, it is apparent that a greater share of earlier studies focused on air travel in North America, whereas later studies have increasingly focused on air travel in other regions. Accordingly, in order to tease the role of *Year* a bit further, we divided the data into estimates from North America and estimates from the rest-of-the-world. Figures 2 and 3 plot the average income elasticity for each study of North America and the rest-of-the-world, respectively, against *Year*. As indicated by the slope of the trend line, the average reported income elasticity estimates for North America have been rising with newer data, whereas those for the rest-of-the-world have been declining. One possible reason for this divergent trend could simply be there is greater prevalence among later studies of North America (rest-of-the-world) to explore less (more) mature market segments, such as international or business travel (domestic or leisure travel). In light of Figures 2 and 3, we re-estimated the general-to-specific meta-regression model allowing for varying trends in the income elasticity. Specifically, we commenced with a general model with all variables included, with two small modifications: we replaced the regional dummies with a single dummy, *Row* (i.e., designating rest-of-the-world), and allowed for varying trends by introducing a year and region interaction term (*Year*Row*). Thus, the coefficient of *Year* reflects the trend in income elasticities for North America, whilst the sum of the coefficients of *Year* and *Year*Row* reflect the trend in income elasticities for the rest-of-the-world. As indicated in column 2 of Table 5, not only are the reported income elasticities larger in North America than the rest-of-the-world (in any given year), but the income elasticities are rising in North America and falling elsewhere. Thus, the difference in the reported income elasticities for North America versus elsewhere is steadily increasing with newer data. Interestingly, the meta-regression results in column 2 of Table 5 also reveal that working papers report larger income elasticities and that a dynamic specification is no longer statistically significant. Other results are similar to those reported in column 1.

Please insert Figures 2 and 3 about here

Fifth, given that many other variables are thrown out in the estimation of the general-to-specific model, several study characteristics are unimportant determinants of the income elasticity. For instance, the income elasticity is largely insensitive to time horizon (i.e., short-run versus long-run delineation), a majority of income measures, data aggregations, and the use of instrumental variables to correct for endogeneity concerns. Regarding time horizon, although Brons et al. (2002) find the price elasticity of air travel is significantly larger (in absolute value) in the long-run, their meta-regression is most comparable to our OLS results in column 1 of Table 4. Indeed, our OLS results indicate the income elasticity of air travel is also significantly larger in the long-run. Yet once WLS and publication selection bias are considered insignificance prevails. Such discrepancies suggest meta-analyses should report results from several alternative specifications when surveying a literature, as discussed by Stanley et al. (2013). As for income measures, Crouch (1992) also finds for international tourism that the income elasticity is insensitive to a majority of income measures; and regarding endogeneity correction, the results might reflect the use of poor instruments, rather than the lack of reverse causation.

Finally, as a robustness check, as mentioned the MRA results in Tables 4 and 5 use 405 observations from the 40 studies for which standard errors were either reported or could be derived. We also re-estimated the MRA using data from all 51 studies initially identified (523 observations). However, since some of these 51 studies do not report standard errors, we are limited to using OLS; and so caution must be taken in directly comparing these results to those in Tables 4 and 5. Nevertheless, we do find many similar results. For example, *OtherLoc* again has a negative coefficient and is the only country dummy with a statistically significant coefficient. *Linear* has a negative coefficient whilst *International* has a positive and statistically significant coefficient. Other results are similar to the OLS results presented in column 1 of Table 4.

CONCLUSION

Our preferred MRA results reveal that the income elasticity is particularly sensitive to a number of features in the literature, as amongst other results we find it to be significantly higher on international routes, yet significantly lower when air fare is included in a dynamic specification of demand. Other features, such as most measures of income, as well as the method used to estimate demand, have less influence the income elasticity.

There are several benefits to now having a better understanding of how changes in consumer income affect the demand for air travel. For instance, given that we find for our preferred MRA that the income elasticity is 1.186 on baseline domestic routes, yet 1.546 on international routes, *ceteris paribus*, this implies demand is much more volatile to changes in income on such routes. As such, during periods of rising income, the distribution of demand will shift away from domestic towards international travel, whilst the opposite holds during periods of falling income. Knowing this, airlines can better adjust marketing strategies in response to income shocks. Also, given that we find the baseline income elasticity falls when air fare is included in a dynamic specification of demand, controlling for these features of demand has an impact on air travel forecasts. For instance, assuming the correct specification of demand should be dynamic and include air fare, then failure to do so would lead to upward bias in air travel forecasts in the presence of positive income shocks. Indeed, with the baseline income elasticity falling from 1.186 to 0.633 when air fare is included in a dynamic specification of demand, a 10 percent increase in income is predicted to increase air travel by 11.86 percent in the former, yet only 6.33 percent in the latter. Not only does this have a sizeable impact on forecasts, but failure to include air fare in a dynamic specification of demand would also lead one to conclude air travel is less mature than it is in reality, thus affecting strategic planning decisions.

Lastly, our MRA results are of specific benefit to researchers in several ways. First, while our results suggest both air fare and income should be included in the specification of air travel demand, the choice of income measure matters less. Second, the multiple MRA results show the literature is free of publication selection bias, and so there is no preferential reporting of income elasticities. This stands in sharp contrast to the situation in many other areas of economics and business literature. Third, based on the results, future primary research may wish to consider why some factors influence income elasticities, whilst others do not. For instance, it would be useful to further examine contemporaneous differences in income elasticities across regions of the world, to see whether or not our failure to identify specific regional differences is simply a historical artifact of the literature. Also, although our literature review indicates that North American income elasticities have slowly increased over time, *ceteris paribus*, it would be interesting to examine in greater detail what is driving this trend. As markets increasingly mature worldwide, it may be that future studies estimate lower income elasticities of demand.

REFERENCES

Alperovich, G., & Machnes, Y. (1994). The role of wealth in the demand for international air travel. *Journal of Transport Economics and Policy*, *28(2)*, 163-173.

Anderson, J.E., & Kraus, M. (1981). Quality of service and the demand for air travel. *Review of Economics and Statistics*, *63(4)*, 533-540.

Angrist, J. D., & Pischke, J-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Bechdolt, B.V. Jr. (1973). Cross-sectional travel demand functions: US visitors to Hawaii, 1961-70. *Quarterly Review of Economics and Business*, *13(4)*, 37-47.

Bhadra, D. (2004). Air travel in small communities: An econometric framework and results. *Journal of the Transportation Research Forum*, *43(1)*, 19-37.

Behbehani, R., & Kanafani, A. (1980). Demand and supply models of air traffic in international markets. Manuscript.

Boeing (2013). *Current Market Outlook: 2013-2032*. Seattle: Boeing.

Britto, R., Dresner, M., & Voltes, A. (2012). The impact of flight delays on passenger demand and societal welfare. *Transportation Research Part E*, *48(2)*, 460-469.

Brons, M., Pels, E., Nijkamp, P., & Rietveld, P. (2002). Price elasticities of demand for passenger air travel: A meta-analysis. *Journal of Air Transport Management*, *8(3)*, 165-175.

Brown, S., & Watkins, W. (1968). The demand for air travel: A regression study of time-series and cross-sectional data in the U.S. domestic market. *Highway Research Record*, *213*, 21-34.

Cameron, A.C., Gelbach, J.B., & Miller, D.L. (2008). Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics*, *90(3)*, 414-427.

Castelli, L., Pesenti, R., & Ukovich, W. (2003). An airline-based multilevel analysis of airfare elasticity for passenger demand. Manuscript.

Chi, J., & Baek, J. (2012). A dynamic demand analysis of the United States air-passenger service. *Transportation Research Part E: Logistics and Transportation Review*, *48(4)*, 755-761.

Crouch, G.I. (1992). Effect of income and price on international tourism. *Annals of Tourism Research*, *19(4)*, 643-664.

Crouch, G.I. (1994). Demand elasticities for short-haul versus long-haul tourism. *Journal of Travel Research*, *33(2)*, 2-7.

Crouch, G.I. (1995). A meta-analysis of tourism demand. *Annals of Tourism Research*, *22(1)*, 103-118.

Dalhuisen, J.M., Florax, R.J.G.M., & de Groot, H.L.F. (2003). Price and income elasticities of residential water demand: A meta-analysis. *Land Economics*, *79(2)*, 292-308.

Dargay, J., & Hanly, M. (2001). The determinants of the demand for international air travel to and from the UK. Manuscript.

Department of Transport (2013). *UK Aviation Forecasts*. London: Department of Transport.

Doucouliagos, H., & Stanley, T.D. (2013). Are all economic facts greatly exaggerated? Theory competition and selectivity. *Journal of Economic Surveys, 27(2)*, 209-394.

Fleming, K., & Ghobrial, A. (1994). An analysis of the determinants of regional air travel demand. *Transportation Planning and Technology*, *18(1)*, 37-44.

Gallet, C.A. (2010). The income elasticity of meat: A meta-analysis. *Australian Journal of Agricultural and Resource Economics*, *54(4)*, 477-490.

Gallet, C.A., & List, J.A. (2003). Cigarette demand: A meta-analysis of elasticities. *Health Economics*, *12(10)*, 821-835.

Garín-Muñoz, T. (2006). Inbound international tourism to Canary Islands: A dynamic panel data model. *Tourism Management*, *27(2)*, 281-291.

Garín-Muñoz, T., & Montero-Martin, L.F. (2007). Tourism in the Balearic Islands: A dynamic model for international demand using panel data. *Tourism Management*, *28(5)*, 1224-1235.

Gately, D. (1987). Taking off: The U.S. demand for air travel and jet fuel. Manuscript.

Ghobrial, A. (1993). A model to estimate the demand between U.S. and foreign gateways. *International Journal of Transport Economics*, 20(3), 271-283.

Gillen, D.W., Morrison, W.G., & Stewart, C. (2007). Air travel demand elasticities: Concepts, issues and measurement. In D. Lee (Ed.), *Advances in Airline Economics Volume 2: The Economics of Airline Institutions, Operations and Marketing* (pp. 365-410). Amsterdam: Elsevier.

Graham, A. (2000). Demand for leisure air travel and limits to growth. *Journal of Transport Management*, *6(2)*, 109-118.

Graham, A. (2006). Have the major forces driving leisure airline traffic changed? *Journal of Transport Management*, *12(1)*, 14-20.

Hazledine, T. (2009). Border effects for domestic and international Canadian passenger air travel. *Journal of Air Transport Management*, *15(1)*, 7-13.

Hedges, L.V., & Olkin, I. (1985). *Statistical Methods for Meta-Analysis*. Orlando, FL: Academic Press.

InterVISTAS Consulting (2007). Estimating air travel demand elasticities. Manuscript.

Ippolito, R.A. (1981). Estimating airline demand with quality of service variables. *Journal of Transport Economics and Policy*, *15(1)*, 7-16.

Jorge-Calderón, J.D. (1996). A demand model for scheduled airline services on international European routes. *Journal of Air Transport Management*, *3(1)*, 23-35.

Klodt, H. (2004). Border effects in passenger air traffic. *Kyklos*, *57(4)*, 519-532.

Knell, M., & Stix, H. (2005). The income elasticity of money demand: A meta-analysis of empirical results. *Journal of Economic Surveys*, *19(3)*, 513-533.

Kopsch, F. (2012). A demand model for domestic air travel in Sweden. *Journal of Air Transport Management*, *20(1)*, 46-48.

Kremers, H., Nijkamp, P., & Rietveld, P. (2002). A meta-analysis of price elasticities of transport demand in a general equilibrium framework. *Economic Modelling*, *19(3)*, 463-485.

Lave, L.B. (1972). The demand for intercity passenger transportation. *Journal of Regional Science*, *12(1)*, 71-84.

Lim, C. (1997). Review of international tourism demand models. *Annals of Tourism Research*, *24(4)*, 835-849.

Lim, C. (1999). A meta-analytic review of international tourism demand. *Journal of Travel Research*, *37(3)*, 273-284.

Liu, H., & Zeng, J. (2007). Airline passenger fatality and the demand for air travel. *Applied Economics*, *39(14)*, 1773-1781.

MacKinnon, J.G., & Webb, M.D. (2013). Wild bootstrap inference for wildly different cluster sizes. Queen's Economics Department Working Paper No. 1314.

Melville, J.A. (1998). An empirical model of the demand for international air travel for the Caribbean region. *International Journal of Transport Economics*, *25(3)*, 313-336.

Moulton, B.R. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *Review of Economics and Statistics, 72(2)*, 334–338.

Mutti, J., & Murai, Y. (1977). Travel on the North Atlantic: Is profitability possible? *Journal of Transport Economics and Policy*, *11(1)*, 45-53.

Nelson, L.A., Dickey, D.A., & Smith, J.M. (2011). Estimating time series and cross section tourism demand models: Mainland United States to Hawaii data. *Tourism Management*, *32(1)*, 28-38.

Oum, T.H., Gillen, D.W., & Noble, S.E. (1986). Demands for fareclasses and pricing in airline markets. *Logistics and Transportation Review*, *22(3)*, 195-222.

Oum, T.H., Waters II, W.G., & 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.

Poole, M., Davis, G., & James, S. (1988). Trends and prospects for Australian international air transport. Manuscript.

Roberts, C.J., & Stanley, T.D. (2005). *Meta-Regression Analysis*. Oxford: Wiley-Blackwell.

Rolls-Royce (2012). *Market Outlook: 2012-31*. Derby: Rolls-Royce.

Rugg, D. (1973). The choice of journey destination: A theoretical and empirical analysis. *Review of Economics and Statistics*, *55(1)*, 64-72.

Saad, M.M., Dao, D.M., McAndrew, R.O., & Watt, S. (1983). Demand for air passenger travel in Australia. Manuscript.

Savage, S., & Dykstra, C. (1995). Demand elasticities for air travel to and from Australia. Manuscript.

Smith, A.B., & Toms, J.N. (1978). Factors affecting demand for international travel to and from Australia. Manuscript.

Song, H., Kim, J.H., & Yang, S. (2009). Confidence intervals for tourism demand elasticity. *Annals of Tourism Research*, *37(2)*, 377-396.

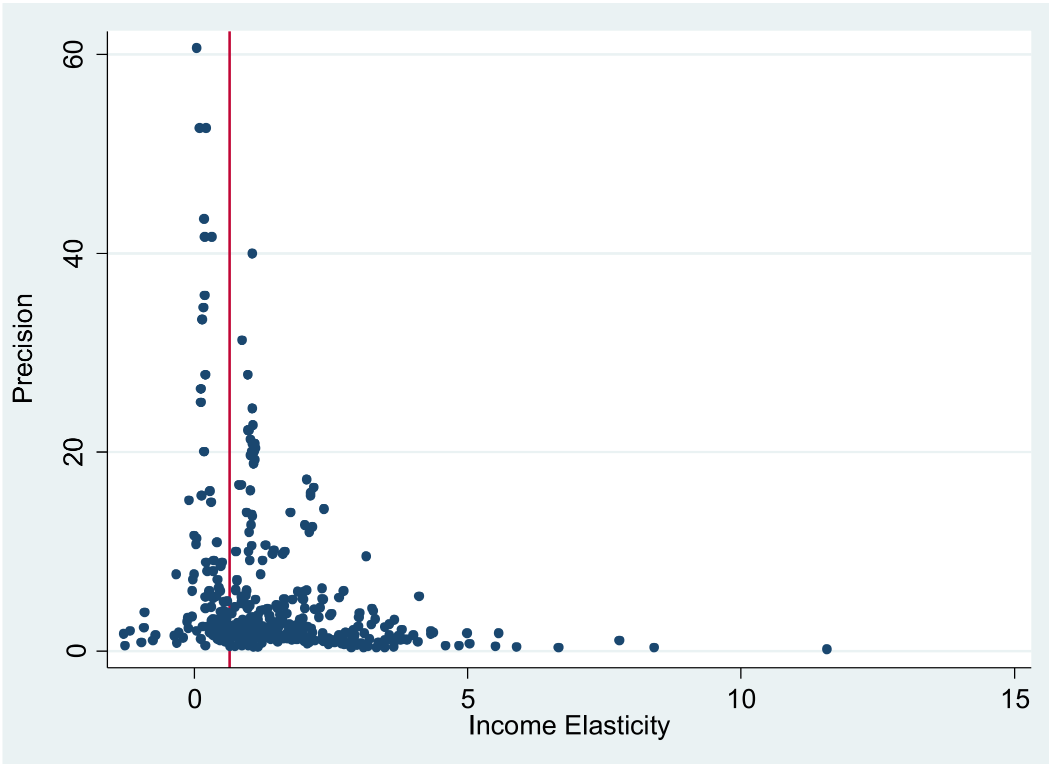
Stanley, T.D. (2008). Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. *Oxford Bulletin of Economics and Statistics*, *70(1)*, 103-127.

Stanley, T.D., & Doucouliagos, H. (2012). *Meta-regression analysis in economics and business.* Oxford: Routledge.

Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J., Johnston, R.J., Laroche, P., Nelson, J.P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R., & Rost, K. (2013). Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys, 27(2)*, 390-394.

Straszheim, M.R. (1978). Demand functions in the North Atlantic and their pricing implications. *Journal of Transport Economics and Policy*, *12(2)*, 179-195.
Streeting, M.C., & Walker, L.G. (1986). Demand for Australian domestic aviation services: Forecasts by market services. Manuscript.
Talley, W.K., & Eckroade, W.R. (1984). Airline passenger demand in monopoly flight segments of a single airline under deregulation. *Transportation Journal*, *24(2)*, 73-79.
Thompson, G.F. (1974). Short-run transport demand at a provincial airport. *Journal of Transport Economics and Policy*, *8(1)*, 70-81.
Thompson, S.G., & Sharp, S.J. (1999) Explaining heterogeneity in meta-analysis: A comparison of methods. *Statistics in Medicine*, *18(20)*, 2693-2708.
Tsekeris, T. (2009). Dynamic analysis of air travel demand in competitive island markets. *Journal of Air Transport Management*, *15(6)*, 267-273.
Verleger Jr., P.K. (1972). Models of the demand for air transportation. *Bell Journal of Economics and Management Science*, *3(2)*, 437-457.
Vitek, R.L., & Taneja, N.K. (1975). The impact of high inflation rates on the demand for airpassenger transportation. Manuscript.
Young, K.H. (1972). A synthesis of time-series and cross-section analyses: Demand for air transportation service. *Journal of the American Statistical Association*, *67(339)*, 560-566.

Figure 1. Funnel Plot of Air Travel Income Elasticities, n = 405



Note: The solid line denotes the position of the precision-weighted average income elasticity (0.64). The vertical axis measures precision calculated as the inverse of the standard error of the income elasticity.

Figure 2. North American Income Elasticity Estimates, Chronological Order

Figure 3. Rest-of-the-World Income Elasticity Estimates, Chronological Order

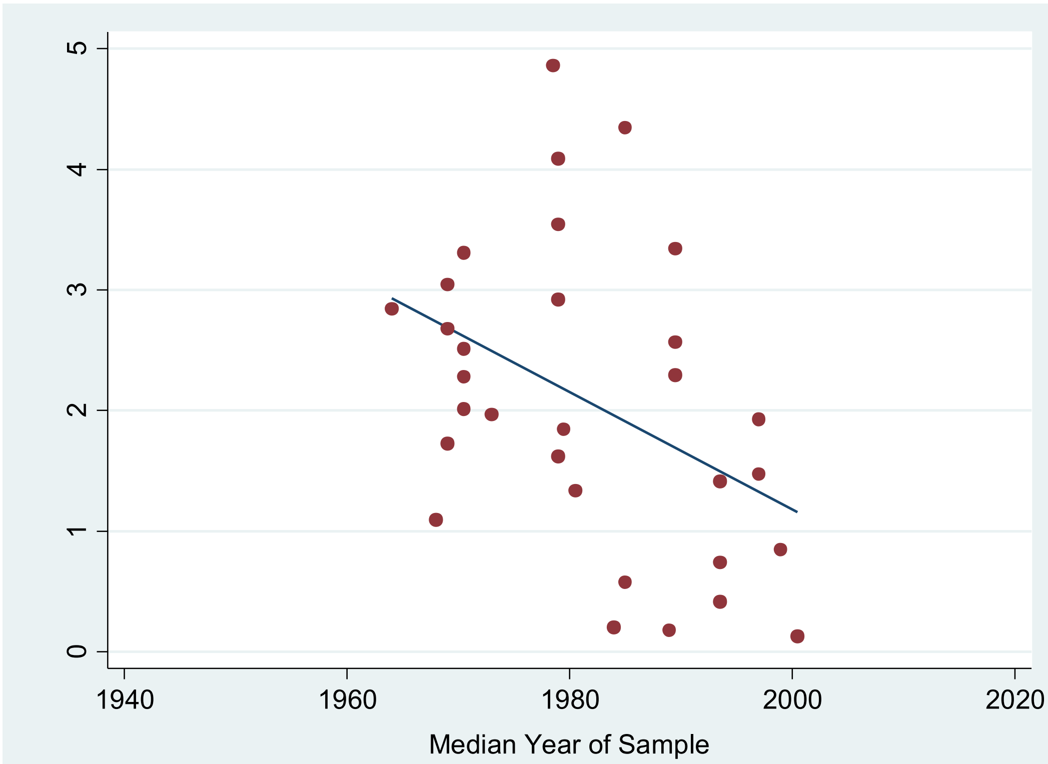


Table 1. Studies included in Meta-Analysis

Study (Year disseminated)	Number of estimates	Mean Income Elasticity
Alperovich and Machnes (1994)	10	1.84
Anderson and Kraus (1981)	16	1.00
Bechdolt (1973)	22	1.94
Behbehani and Kanafani (1980)	4	1.96
Bhadra (2004)	2	4.66
Britto, Dresner, and Voltes (2012)	3	2.51
Brown and Watkins (1968)	5	1.00
Castelli, Pesenti, and Ukovich (2003)	1	0.26
Chi and Baek (2012)	1	3.74
Dargay and Hanly (2001)	4	1.08
Fleming and Ghobrial (1994)	2	0.06
Garín-Muñoz (2006)	9	1.93
Garín-Muñoz and Montero-Martin (2007)	2	1.47
Gately (1987)	12	2.23
Ghobrial (1993)	1	2.11
Hazledine (2009)	6	0.56
InterVISTAS Consulting (2007)	8	0.27
Ippolito (1981)	1	2.35
Jorge-Calderón (1996)	6	0.18
Klodt (2004)	6	0.85
Kopsch (2012)	4	0.41
Lave (1972)	6	1.80
Liu and Zheng (2007)	8	1.22
Melville (1998)	15	0.48
Mutti and Murai (1977)	15	2.32
Nelson, Dickey, and Smith (2011)	15	1.08
Oum, Gillen, and Noble (1986)	2	1.76
Poole, Davis, and James (1988)	7	0.55
Rugg (1973)	13	3.04
Saad, Dao, McAndrew, and Watt (1983)	6	3.26
Savage and Dykstra (1995)	21	2.76
Smith and Toms (1978)	15	2.42
Staszheim (1978)	1	1.09
Streeting and Walker (1986)	55	1.33
Talley and Eckroade (1984)	6	1.84
Thompson (1974)	4	2.84
Tsekeris (2009)	7	0.20
Verleger (1972)	10	0.87
Vitek and Taneja (1975)	68	0.91
Young (1972)	6	1.76

Note: Year disseminated corresponds to year published or year completed (for working papers).

Table 2. Independent Variables

Variable	Definition (mean μ, standard deviation σ)
Location:	
North America	= 1 if income elasticity corresponds to North America (μ = 0.50, σ = 0.50)
Asia	= 1 if income elasticity corresponds to Asia (μ = 0.03, σ = 0.17)
AustNZ	= 1 if income elasticity corresponds to Australia/New Zealand (μ = 0.20, σ = 0.40)
Europe	= 1 if income elasticity corresponds to Europe (μ = 0.18, σ = 0.38)
OtherLoc	= 1 if income elasticity corresponds to other locations (μ = 0.09, σ = 0.29)
Route:	
Domestic	= 1 if income elasticity corresponds to domestic flight (μ = 0.67, σ = 0.48)
International	= 1 if income elasticity corresponds to international flight (μ = 0.33, σ = 0.47)
Specification:	
Linear	= 1 if demand is linear (μ = 0.02, σ = 0.16)
Double-Log	= 1 if demand is double-log (μ = 0.98, σ = 0.15)
Fare	= 1 if demand includes air fare (μ = 0.75, σ = 0.43)
Static	= 1 if demand is static (μ = 0.75, σ = 0.43)
Dynamic	= 1 if demand is dynamic (μ = 0.25, σ = 0.43)
Short-run	= 1 if income elasticity pertains to short-run (μ = 0.89, σ = 0.32)
Long-run	= 1 if income elasticity pertains to long-run (μ = 0.11, σ = 0.31)
Income Origin	= 1 if income is at location where flight originates (μ = 0.77, σ = 0.42)
Income Product	= 1 if income is product of origin and destination incomes (μ = 0.06, σ = 0.23)
Income	= 1 if income is average of the origin and destination incomes (μ = 0.08, σ = 0.27)
Average	= 1 if income is sum of origin and destination incomes (μ = 0.03, σ = 0.18)
Income Sum	= 1 if income is proxied by consumer expenditure (μ = 0.06, σ = 0.25)
Expenditure	
Data/Estimation:	= 1 if time-series data used to estimate demand (μ = 0.55, σ = 0.50)
Time	= 1 if cross-sectional data used to estimate demand (μ = 0.21, σ = 0.41)
Cross	= 1 if panel data used to estimate demand (μ = 0.24, σ = 0.43)
Panel	= 1 if data aggregated to country-level (μ = 0.50, σ = 0.50)
Country	= 1 if data aggregated to state-level (μ = 0.10, σ = 0.30)
State	= 1 if data aggregated to city-pair level (μ = 0.34, σ = 0.47)
City	= 1 if data aggregated to other level (μ = 0.06, σ = 0.24)
OtherAgg	= 1 if instrumental variables used to estimate demand (μ = 0.13, σ = 0.33)
IV	
Others:	Standard error of income elasticity (μ = 0.55, σ = 0.62)
Standard error	= 1 if study is working paper (μ = 0.50, σ = 0.50)
Work	Median year of the sample used to estimate demand (μ = -1.79, σ = 14.03)
Year	

Notes: For several categories (e.g., location and route), since the variables encompass all observations, the means sum to 1 (although there are slight discrepancies above due to round-off error). A few income elasticity estimates were not classified by study authors as either international or domestic, which were classified under the baseline Domestic above. Year is measured as deviations of the median sample year from 1978, the mean year across all observations.

Table 3. Meta-Average Income Elasticities and Publication Selection Bias Tests
(Dependent variable is income elasticity)

	Simple average (1)	Weighted average (2)	FAT-PET (3)	PEESE (4)
Income elasticity	1.517 (1.17 to 1.85)	0.642 (0.31 to 0.97)	0.474 (0.13 to 0.82)	0.696 (0.33 to 1.06)
Standard error	-	-	2.991 (1.46 to 4.52)	-
Standard error squared	-	-	-	1.242 (0.29 to 2.19)
Adjusted R^2			0.14	0.02

Notes: The number of observations is 405 from 40 studies. The dependent variable in all columns is the income elasticity. Column 1 reports the simple (unweighted) average income elasticity. Column 2 reports the weighted average income elasticity, with the inverse variance as weights. Column 3 reports the results from the FAT-PET model, while column 4 reports the results from the PEESE model. Columns 3 and 4 are estimated using weighted least squares (WLS), with the inverse variance as weights. Parentheses report 95% confidence intervals, derived using standard errors corrected for the clustering of observations within studies.

Table 4. Fully Specified Meta-Regression Results
(Dependent variable is income elasticity)

Variable	OLS (1)	WLS (2)	WLS (3)	WLS (4)
Constant	1.049 (0.011)	1.205 (0.000)	1.205 (0.002)	1.205 (0.050)
Standard Error	1.204 (0.000)	1.038 (0.001)	1.038 (0.390)	1.038 (0.590)
Location:				
Asia	0.599 (0.382)	-0.303 (0.534)	-0.303 (0.605)	-0.303 (0.715)
AustNZ	-0.087 (0.820)	-0.545 (0.002)	-0.545 (0.053)	-0.545 (0.155)
Europe	0.099 (0.360)	-0.694 (0.000)	-0.694 (0.023)	-0.694 (0.105)
OtherLoc	-0.444 (0.134)	-0.700 (0.000)	-0.700 (0.001)	-0.700 (0.040)
Route:				
International	0.672 (0.018)	0.532 (0.001)	0.532 (0.052)	0.532 (0.235)
Specification:				
Linear	-0.785 (0.021)	-1.427 (0.000)	-1.427 (0.009)	-1.427 (0.030)
Fare	0.100 (0.705)	-0.473 (0.000)	-0.473 (0.001)	-0.473 (0.025)
Dynamic	-0.394 (0.312)	-0.644 (0.004)	-0.644 (0.076)	-0.644 (0.155)
Long-run	0.694 (0.003)	-0.098 (0.290)	-0.098 (0.218)	-0.098 (0.165)
Income Product	0.267 (0.388)	0.029 (0.706)	0.029 (0.722)	0.029 (0.830)
Income Average	0.769 (0.045)	-1.026 (0.000)	-1.026 (0.007)	-1.026 (0.035)
Income Sum	-1.225 (0.035)	0.953 (0.000)	0.953 (0.020)	0.953 (0.140)
Expenditure	0.057 (0.881)	0.080 (0.705)	0.080 (0.604)	0.080 (0.555)
Data/Estimation:				
Time	0.243 (0.167)	0.599 (0.006)	0.599 (0.037)	0.599 (0.095)
Cross	-0.699 (0.057)	-0.114 (0.199)	-0.114 (0.096)	-0.114 (0.185)
Country	-0.270 (0.530)	0.417 (0.145)	0.417 (0.282)	0.417 (0.440)
State	0.899 (0.096)	0.109 (0.629)	0.109 (0.741)	0.109 (0.835)
City	-0.343 (0.417)	-0.278 (0.189)	-0.278 (0.318)	-0.278 (0.480)
IV	-0.866 (0.056)	0.373 (0.073)	0.373 (0.075)	0.373 (0.140)
Others:				
Work	-0.386 (0.234)	0.029 (0.815)	0.029 (0.839)	0.029 (0.815)
Year	-0.001 (0.933)	0.013 (0.000)	0.013 (0.001)	0.013 (0.020)
F-test (p-value)	930.47 (0.000)	107.23 (0.00)	5237.38 (0.00)	
Adjusted R^2	0.42	0.73	0.73	0.73

Notes: The number of observations is 405 from 40 studies. Cell entries in parentheses report p-values. Column 1 uses OLS with standard errors adjusted for data clustering at the study level to construct p-values. Weighted least squares (WLS) used to estimate columns 2 to 4, with the inverse variance as weights. Column 2 uses robust standard errors to construct p-values. Column 3 uses standard errors adjusted for data clustering at the study level to construct p-values. Column 4 uses the Cameron et al. (2008) wild bootstrap-t method to derive the standard errors used to construct p-values. All bootstrapping uses 400 replications. F-test refers to a test of the joint significance of the estimated coefficients.

Table 5. General-To-Specific Meta-Regression Results
(Dependent variable is income elasticity)

Variable	WLS (1)	WLS (2)
Constant	1.186 (0.000)	1.319 (0.000)
Standard Error	-	-
Location:		
Asia	-	-
AustNZ	-	-
Europe	-	-
OtherLoc	-0.263 (0.060)	-
Row	-	-0.334 (0.005)
Route:		
International	0.360 (0.005)	0.465 (0.005)
Specification:		
Linear	-1.737 (0.005)	-2.090 (0.005)
Fare	-0.278 (0.005)	-0.568 (0.005)
Dynamic	-0.275 (0.010)	-
Long-run	-	-
Income Product	-	-
Income Average	-0.774 (0.030)	-0.825 (0.040)
Income Sum	-	-
Expenditure	-	-
Data/Estimation:		
Time	0.852 (0.000)	0.903 (0.000)
Cross	-	-
Country	-	-
State	-	-
City	-0.581 (0.005)	-0.289 (0.060)
IV	-	-
Others:		
Work	-	0.272 (0.040)
Year	0.005 (0.020)	0.015 (0.000)
Year*Row	-	-0.022 (0.005)
Adjusted R^2	0.68	0.73

Notes: The number of observations is 405 from 40 studies. Cell entries in parentheses report p-values. Weighted least squares (WLS) used to estimate columns 1 and 2, with the inverse variance as weights. Cameron et al. (2008) wild bootstrap-t method used to derive the standard errors in the construction of p-values. All bootstrapping uses 400 replications. Column 1 reports the specific MRA counterpart to the Table 4 meta-regressions, whilst column 2 reports the specific MRA allowing for differences in trends between North America and the rest-of-the-world.