Rank-Order Concordance Among Conflicting Emissions Estimates for Informing Flight Choice

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this version: November 29, 2016

Abstract

Air transport Greenhouse Gas (GHG) emissions estimates differ greatly, depending on the calculation method employed. Among the IPCC, ICAO, DEFRA, and BrighterPlanet calculation methods, the largest estimate may be up to 4.5 times larger than the smallest. Such heterogeneity – and ambiguity over the true estimate – confuses the consumer, undermining the credibility of emissions estimates in general. Consequently, GHG emissions estimates do not currently appear on the front page of flight search-engine results. Even where there are differences between alternative flights' emissions, this information is unavailable to consumers at the point of choice. When external considerations rule out alternative travel-modes, the *relative ranking* of flight options' GHG emissions is sufficient to inform consumers' decision making. Whereas widespread agreement on a gold standard remains elusive, the present study shows that the principal GHG emissions calculation methods produce consistent rankings *within specific route-structure classes*. Hence, for many consumers, the flight identified as most GHG efficient is not sensitive to the specific calculation method employed. But unless GHG emissions information is displayed at the point of decision, it cannot enter into consumers' decision making. A credible and ambiguity-free alternative would thus be to display GHG *ranking* information on the front page of flight search-engine results.

Keywords: greenhouse gas emissions, carbon footprint computation, scheduled passenger air transport, informed choice, decision making, behavior, policy

JEL classification: Q54, D62, D03

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1 Introduction

At the point of decision, consumers are generally not provided with the GHG emissions information required to make an environmentally responsible choice between different flight options. Flight search engines typically display GHG information, if at all, on CO_{2e}-offset pages which are reached after a specific flight has been selected for purchase. Given differences between emissions calculation methods and differing views on Radiative Forcing (RF), any one CO_{2e} calculator confers advantage to some flights and disadvantage to others in a manner that, to an airline company, may appear arbitrary and unwelcome. For competitive reasons, airlines have been reluctant to elevate GHG emissions to be front-page product-defining attributes alongside price and convenience. Multiple-methods, multiple-estimates ambiguity is a major impediment to the promotion of CO_{2e} to the front page of flight search-engine results, where it must appear in order to have an impact upon consumers' choices.[1]

In this study we document the degree of heterogeneity in the estimated emission *levels* calculated with different methods. We then investigate the linear association between and *rank-order* concordance among different methods' estimates. We do so both through examining the calculation methods' formulae as well as through statistical analysis of flight data, including a broad, representative global sample drawn from IATA's World Air Transport Statistics.

In Section 2 we review previous research on flight-level GHG emissions estimates, and in Section 3 we discuss four calculation methods in detail: DEFRA, ICAO, BrighterPlanet, and EEA/IPCC. In Section 4 we report statistical analysis and testing of linear association between – and rank-order concordance among – the different methods. Section 5 concludes.

2 Previous research

Civil aviation GHG emissions are estimated as global-level inventories (Olivier, 1995; IPCC, 1999; Wilkerson et al., 2010; Simone et al., 2013; Wasiuk et al., 2015), regional-level inventories (Wasiuk et al., 2015), national-level inventories (Pejovic et al., 2008; GAO, 2009), airport-level inventories (Hudda et al., 2014; Sherry, 2015), airline-level inventories (Miyoshi and Mason,

[1]We thank one of our anonymous Reviewers for pointing out that some airlines do make attempts to communicate flights' emissions to customers, through e.g. eco-labelling schemes or in connection with carbon off-setting schemes. However, this falls short of appearing on the front page of search-results screens – i.e. at the point of decision – of flight-search engines which aggregate across airlines and airline alliances.

2009; van Dorland et al., 2009; Zou et al., 2012), and as performance statistics for individual engines or aircraft (Green, 2002; DuBois and Paynter, 2006). At each of these levels there is a well-defined clientele for these emissions-estimate data, and hence there is a substantial volume of research being continually conducted and published on all of these levels. Within tourism research, emissions-offsetting schemes and the GHG-emissions calculators they employ have been investigated by a variety of authors, including e.g. Gössling et al. (2007). Other strands of literature examine consumers' understanding of transportation CO_2 information when, as is typically the case, it is presented in mass units (Coulter et al., 2007), as well as the effectiveness of different contextualization and 'nudge' devices for enhancing the behavioral impact of transport CO_2 information (Waygood et al., 2012; Avineri and Waygood, 2013). For numerous reasons – participation in a regional emissions-trading scheme (e.g. the EU Emissions-Trading Scheme), meeting carbon-reduction targets, and the study of transport-mode choice for informing transport policy – GHG emissions have become the subject of a vast volume of transport research.

In stark contrast, research on flight-level GHG emissions-calculation methods – for informing consumers at the point-of-choice – is exceptionally sparse. Moreover, this research remains within the grey literature (institutional reports), despite point-of-choice GHG-emissions calculation being the necessary input for making environmentally responsible decisions when purchasing flights through flight-search engines, and despite the transport-research field recognizing point-of-choice influence as being an environmentally consequential and legitimate research question in its own right (see e.g. Avineri and Waygood, 2013).

These grey-literature studies originate from the Stockholm Environment Institute (Kolmuss and Lane, 2008; Kolmuss and Myers Crimmins, 2009), the Oxford Environmental Change Institute (Jardine, 2009), and the Breda Centre for Sustainable Tourism & Transport (Eijgelaar et al., 2013). Common to these studies is the aim to identify the best calculation method, if such an optimal method exists and is discernible as such. The calculators – and the studies at least in part – are motivated by GHG-emissions off-setting systems' requirements for such estimates, by GHG-emissions accounting and reporting requirements, and by teleological reasoning fixed on the objective of having travel-mode choices respond to flight-specific GHG emissions.

These studies document great differences between the flight-specific estimates provided by the existing GHG-emissions calculation methods. They conclude that, whereas different calculation methods have different advantages and strengths,[2] ultimately all of the calculation methods are imperfect and involve strong compromises.

Whereas we discuss the calculation methods in detail below (Section 3), here we note two sources of uncertainty emphasized in the grey-literature studies. First, aside from any inaccuracies in the raw input information regarding plane type and its engines,[3] actual emissions will deviate from calculated emissions because of (i) variation in climatic conditions, such as headwinds or tailwinds, (ii) variation in flight distances and paths, due e.g. to weather-related routing, (iii) variation in time spent in the holding-pattern 'stack', and (iv) variation in the mass of the aircraft from one flight to the next (Jardine, 2009). These sources of irreducible variation entail that there are limits to the precision with which realized GHG emissions may be estimated ex ante. Second, there are numerous metrics with which to adjust airliner CO_2 estimates to account for non-CO_2 effects[4]: Radiative Forcing (RF),[5] Radiative Forcing Index (RFI), Integrated Radiative Forcing (IRF), Global Warming Potential (GWP), Global Temperature Change Potential (GTP), and Integrated Change in Temperature over Time (ICTT) (Kolmuss and Myers Crimmins, 2009). The most commonly used adjustment metric is RFI, which is defined as the ratio of total RF to RF from CO_2 emissions alone. The RFI value used in some calculators may be as high as 4 (Jardine, 2009). However most pre-2005 implementations employed the IPCC (1999) report's central estimate of 2.7, and most post-2005 implementations employ Sausen et al.'s (2005) updating of the original IPCC estimate to 1.9.

Nevertheless in a strict technical sense RFI is a fundamentally flawed metric for gauging the impact of individual flights in the future, as RFI (i) is based on the cumulative effect of past emissions, (ii) is not independent of background atmospheric conditions, and (iii) is not able to account for the different latency periods of different forcing agents (Jardine, 2009; Kolmuss and Myers Crimmins, 2009; Peeters and Williams, 2009; Eijgelaar et al., 2013).

Despite the improvements that GWP, GTP and ICTT bring over RFI, considerable uncer-

[2]for instance some utilize extensive detailed information about the flight, whereas at the other extreme some methods employ simple, robust calculations with low informational requirements

[3]Due to operational exigencies, airlines will occasionally substitute one aircraft with another that is not a precise match down to airframe model and variant, engine type, vintage and efficiency.

[4]emission of water vapour (H_2O), nitrogen oxides (NO_x), particulates (sulfates and soot aerosols), and the formation of contrails and cirrus clouds

[5]The RF of a forcing agent (a gas) is the difference between incoming solar radiation and outgoing infrared radiation, expressed in Watts per square meter (W/m^2).

tainty and lack of precision remains. In part, this is due to "the relatively low understanding of the impact of contrails and contrail-induced cirrus on radiative forcing and the feedback loops between climate change and the local and global occurrence of these aviation-related impacts" (Peeters et al., 2007). Furthermore, each adjustment-metric implementation involves making an assumption regarding the horizon over which it is to be calculated. Hence each metric can generate a range of different estimates, depending on the horizon assumed in calculation. This in turn needs to be determined to match the duration(s) of the forcing agent(s) that the analyst wishes to capture. For instance Kolmuss and Myers Crimmins (2009) advocate a short time horizon of e.g. 20 years to capture the more short-lived effects. These authors acknowledge that "this is a value-based choice... ...in order to best estimate [sic] the footprint of an individual or company due to their current air travel" (Kolmuss and Myers Crimmins, 2009).

While acknowledging the fundamentally flawed nature of RFI for gauging the prospective climate-change impact of individual flights, the grey-literature studies concur that a multiplier greater than 1 should be employed to account for non-CO_2 effects (Kolmuss and Myers Crimmins, 2009; Eijgelaar et al., 2013). The value recommended for this multiplier is in the 1.9–2 range (Kolmuss and Myers Crimmins, 2009). Implicitly, therefore, RFI is accepted as a pragmatic compromise solution. Subsequent studies have adopted RFI as a compromise solution between reliability and usefulness (Eijgelaar et al., 2013, p. 70).

Whereas the existing literature acknowledges the dispersion in estimates calculated with different methods, it has not attempted to address the associated problems of credibility and confusion that impede their adoption for front-page, point-of-choice display. The purpose of the present study is to resolve these problems of logical credibility and mixed messages for point-of-choice display.

3 Calculation methods

According to general guidance issued by the Intergovernmental Panel on Climate Change (IPCC), the GHG emissions of scheduled commercial passenger air transport depends on a variety of factors including the type and efficiency of the aircraft and its engines, fuel consumption, distance flown, the composition of the flight in terms of take-off, climb, cruise, decent & landing operating phases, the engine power settings in these operating phases, and flight altitude, among others.

There are several methods for calculating the carbon emissions of a specific flight. In practice the choice of method depends primarily on data availability and the accuracy required. Here we introduce four of the most commonly cited methods. The principal distinction is between methods that employ a fuel-based approach and those that employ a distance-based approach.

We begin with the EEA/IPCC approach, which is *conceptual* and *general* in distinguishing between Tier-1 (fuel-based) calculations, Tier-2 (fuel-based, differentiated by whether burn takes place in the cruise phase, or in Landing/Take-Off phase), and Tier-3 (distance-based, flight-cycle-phase sensitive, differentiated by aircraft-and-engine type and origin-destination pair) calculations. We then introduce operational implementations of these approaches, all of which infer fuel burn from distance flown: DEFRA (Tier 1), ICAO (coarse-grained Tier 3), and BrighterPlanet (fine-grained Tier 3).

A The European Environment Agency (EEA) and the IPCC both follow a 3-Tier approach to the calculation of carbon emissions for scheduled commercial air transport (EMEP/EEA, 2009; IPCC, 2006). The approach is *conceptual* and *general*. As long as the appropriate emission factor is used, the approach can be applied to direct flights as well as to the individual legs of a multi-segment flight. Equally, it can be used for calculating CO_2 emissions or CO_{2e} emissions.

Tier 1 is a purely fuel-based approach, where total emissions are obtained by multiplying fuel consumption with an emission factor.

$$\text{Emissions } (CO_2 \text{ or } CO_{2e}) = \text{Fuel Consumption} \times \text{Emission Factor} \tag{1}$$

Tier 2, also a fuel-based approach, accounts for the fact that jet engines have higher emissions during the Landing/Take-Off (LTO) phase than during the cruise phase of flight. In this approach, total emissions are the sum of LTO emissions and cruise emissions, which are calculated respectively by multiplying LTO fuel consumption with the LTO emission factor and multiplying cruise fuel consumption with the cruise emission factor.

$$
\begin{aligned}
\text{Total emissions} &= \text{LTO Emissions} + \text{Cruise Emissions} && (2)\\
\text{LTO Emissions} &= \text{LTO Fuel Consumption} \times \text{Emission Factor LTO} && (3)\\
\text{Cruise Emissions} &= \text{Cruise Fuel Consumption} \times \text{Emission Factor Cruise} && (4)\\
\text{Cruise Fuel Consumption} &= \text{Total Fuel Consumption} - \text{LTO Fuel Consumption} && (5)\\
\text{LTO Fuel Consumption} &= \text{Number of LTOs} \times \text{Fuel Consumption per LTO} && (6)
\end{aligned}
$$

Tier 3 follows a distance-based approach where origin- and destination-airport information is utilized. The specific aircraft type is then found from an appropriate database. Again the LTO fuel consumption and cruise fuel consumption are calculated for the specific engine and total emissions are the sum of LTO emissions and cruise emissions.

B The UK Department for Environment, Food and Rural Affairs (DEFRA) method employs a linear distance-based approach, where the impacts of CO_2, CH_4 and N_2O are included (DEFRA, 2011). DEFRA recommends a 1.9 multiplier if the impact of water vapor, contrails and NO_x are to be included. The distance of the flight is multiplied by an emission factor as follows to obtain an estimate of the CO_2-equivalent (CO_{2e}) emissions:

$$\text{Emissions } (CO_{2e}) = \text{Distance (km)} \times \text{Emission Factor} \quad (7)$$

This emission factor incorporates a 9% uplift to account for delays/circling and route deviations from the Great Circle Distance (GCD) lines between destinations, following IPCC recommendations. In the 2011 DEFRA guidelines the average value of the emission factor is set to be 164.84g/km for UK domestic flights, 96.84g/km for European flights (or distances up to 3700km), and 111.48g/km for all other international flights (or distances above 3700km) (DEFRA, 2011). These values are calculated based on a flight length from the EMEP/EEA Guidebook of 463km, 1108 km and 6482km respectively (EMEP/EEA, 2009).

C The International Civil Aviation Organization (ICAO) adopts a more sophisticated distance-based approach, where each calculation is based on the origin and final destination airports for direct flights, and on the chain of airport pairs for indirect flights (ICAO, 2012). Then published scheduled flights data are used to obtain the aircraft type, which is mapped onto one of fifty 'equivalent type' classes for the purpose of calculating fuel consumption. When a unique aircraft type cannot be identified and scheduled flight data identify a set of possible aircraft types, fuel consumption is estimated as the frequency-weighted average of the fuel consumptions over this set of potential aircraft types. The GCD method is used to calculate the flight distance. ICAO collects passenger load factor data and passenger-to-cargo-ratio data. These variables are used to calculate the average fuel consumption per economy class passenger. The fuel consumption is then multiplied by 3.157 (representing the number of tonnes of CO_2 produced by burning one tonne of aviation fuel) to obtain the average CO_2 footprint per economy class passenger.

D BrighterPlanet characterizes flights by origin airport, destination airport, distance, airline, aircraft, seat class, load factor and round-trip versus one-way, and other variables (Kling and Hough, 2010). The BrighterPlanet methodology is also distance-based. The main innovation of this method is that it allows additional parameters (seat class, round-trip versus one-way, etc.) instead of relying on averages over these parameters. For indirect flights the method can be applied to each segment separately.

With the origin-destination parameters for any flight, the passenger-specific emissions are calculated as follows

$$\text{Emissions} = \frac{\text{Total Fuel}}{\text{Passengers}} \times \text{Seat Class Multiplier} \times (1 - \text{Freight Share}) \times \text{EF} \times \text{RFI} \tag{8}$$

where the emission factor (EF) is taken from the U.S. Energy Information Administration (EIA)[6] and a radiative forcing index (RFI) of 2 is used to incorporate the effects of high-altitude emissions and contrails. Seat-Class Multiplier is calculated using data from SeatExpert and SeatGuru. Freight Share and Passengers are calculated as passenger-weighted averages of coresponding values of all flights matching this origin-destination

[6] `www.eia.gov`

pair. Total Fuel is calculated as

$$\text{Total Fuel} = \text{Fuel per Segment} \times \text{Segments} \times \text{Trips} \tag{9}$$

$$\text{Fuel per Segment} = b + (m_1 \times d_s) + (m_2 \times d_s^2) + (m_3 \times d_s^3) \tag{10}$$

$$d_s = 1.07 \times \frac{\text{Distance}}{\text{Segments}} \times 1.25^{(\text{Segments}-1)} \tag{11}$$

where coefficients b, m_1, m_2, m_3 are calculated by fitting a third-order polynomial equation to the EEA fuel-consumption data.

4 Analysis

4.1 A priori analysis

The above-documented diversity in calculation methods leads to large differences in the levels of estimated CO_{2e}. In Case 1 examined below, the largest estimates are 4.0 times the smallest. In Case 3 the largest estimates are 4.5 times the smallest (excluding a small number of outliers, the largest of which is 14.1). This is larger than the factor-of-three maximum deviation previously cited by Kolmuss and Lane (2008).

The diversity in calculation methods nevertheless accommodates high between-method correlations. For instance, the DEFRA method can be classed as an implementation of EEA/IPCC Tier 1 methodology, operationalized by assuming that fuel consumption is piece-wise linear in flight distance. This may be seen as coarsely capturing non-linearity of fuel consumption with increasing distance via the effect of various factors, including aircraft design range and the difference between the LTO and cruise phases of flight. The ICAO method can be classed as a coarse-grained implementation of the EEA/IPCC Tier 3 methodology, which uses 50 aircraft type classes and route-specific averaging to estimate fuel consumption and emission factors as linear functions of segment length. Finally, the BrighterPlanet method can be classed as a fine-grained implementation of the EEA/IPCC Tier 3 methodology, using finer-grained data and a more complicated estimation formula, including non-linear (third-degree-polynomial) representation of the relationship between segment length and fuel burn and its associated emissions.

More generally, the fuel-based approach and the distance-based approach share the common principle that fuel consumption should be multiplied and/or divided by a number of factors to generate the emissions estimate. These factors include: the emission factor, the passenger load factor, and the passenger-to-cargo ratio, among others. The main difference lies only in the fact that the distance-based approach requires additional information – e.g. on the origin and destination airports and aircraft type – in order to estimate fuel consumption more precisely. If fuel consumption is indeed approximately a linear function of flight distance,[7] an equivalency can be established between the fuel-based approach and the distance-based approach, with the qualification that the latter requires more information and leads to more accurate estimates.

BrighterPlanet estimates are consistently higher than those generated with the DEFRA and ICAO methods. Whereas the DEFRA and ICAO methods are restricted to direct emissions, the BrighterPlanet method also comprehensively incorporates factors contributing to *indirect* CO_{2e} emissions. These include the effects of methane, nitrous oxide, sulfur hexafluoride, hydrofluorocarbons, perfluorocarbons, land-use change, radiative forcing (a multiplier of 2 rather than 1.9), and *indirect supply-chain emissions from the production of goods and services used as inputs in the provision of air transport services.* These indirect – a.k.a. embodied – emissions often account for a large fraction of total emissions (Kling and Hough, 2010).

A premium-class ticket entitles the traveller to a larger floor footprint as well as a larger non-baggage weight overhead.[8] The opportunity cost of the extra floor-space taken by premium-class travellers is additional standard-class travellers. But an additional standard-class traveller typically brings not only her own bodyweight onboard, but also her own luggage. Different emissions-calculation methods determine the trade-off between floor-space and weight differently, resulting in different seat-class multipliers. Standard-class seats receive a multiplier of 1, and premium-class seats received a higher multiple (> 1). The DEFRA method allocates business-class seats a multiplier of 2.9, and first-class seats a multiplier of 4. The BrigherPlanet method calculates premium-class seat multipliers based on weighted[9] average seat area specific to each airline-aircraft configuration. In turn, the ICAO method allocates flight-specific emissions between economy- and premium-class seats in the ratio of 1:2.

[7]Analysis of EEA fuel consumption data *within aircraft types* reveals a strong linear relationship between distance flown and fuel consumption. The EEA data is available at `http://www.eea.europa.eu/publications/emep-eea-emission-inventory-guidebook-2009/part-b-sectoral-guidance-chapters/1-energy/1-a-combustion/1-a-3-a-aviation_annex.zip`

[8]a larger, heavier seat; a heavier catering package; a higher bathroom-to-passenger ratio (augmenting both traveler-specific weight and floor-space overhead); a higher flight-attendant-to-passenger ratio (augmenting traveller-specific weight)

[9]by annual traffic volume

In the sequel, we restrict empirical analysis to standard-class (economy) seats. The intention is to study the like-with-like comparisons of typical flight-search-engine users who face a tradeoff between price and GHG emissions. Premium-class seats are dominated by standard-class seats in both price and GHG emissions.

4.2 Empirical analysis

Given the relative paucity of existing multivariate statistical analysis across the different methods, the task here is two-fold: first, inductive development of empirical-regularities hypotheses; second, empirical testing of these hypotheses on a broad, representative sample. For the former, we employ tractable, focussed datasets. Due to the funding under which this project was conducted[10] and a commitment to undertaking research that is of relevance beyond London's super hubs, we source our inductive-development datasets from among flights originating at Manchester International Airport, which is the UK's largest regional airport outside London. The selection conditions applied in constructing the Case 1 dataset restrict heterogeneity, yielding a relatively homogeneous set of flights between Manchester (MAN) and New York (NYC). This dataset is instrumental for demonstrating and illustrating rank-order equivalence, but begs the question of whether rank-order equivalence holds in samples incorporating more heterogeneity, especially route-structure heterogeneity. The Case 2 dataset's selection conditions are designed to ensure such heterogeneity, and are verifiably embodied in the sample of flights between Manchester (MAN) and Kuala Lumpur (KUL). Finally, the discovered empirical regularities are tested on the Case 3 broad-based sample drawn from IATA's World Air Transport Statistics (WATS), which is documented in Appendix A.

Given that the EEA/IPCC approach is conceptual and general, in the empirical analysis below we focus on widely available online calculators that implement operationally different tiers of the EEA/IPCC approach: DEFRA, ICAO, and BrighterPlanet.

4.2.1 Case 1: MAN-NYC

Consider the task of choosing among different flight options from Manchester UK to New York. We collect data for 27 different route-time-airline combinations departing between 9am and

[10]Research Councils UK research grant number EP/I00033X/1

12am on May 1st 2013. For present purposes, only flights of no more than 24 hours duration are considered. Flights that involve three or more transfers are excluded. Flights with prices above 1000GBP are excluded.

The price (on the horizontal axis) and carbon emissions (on the vertical axis) pairs for all 27 flights are plotted in Figure 1, where the emissions are calculated by the BrighterPlanet, DEFRA and ICAO methods respectively.

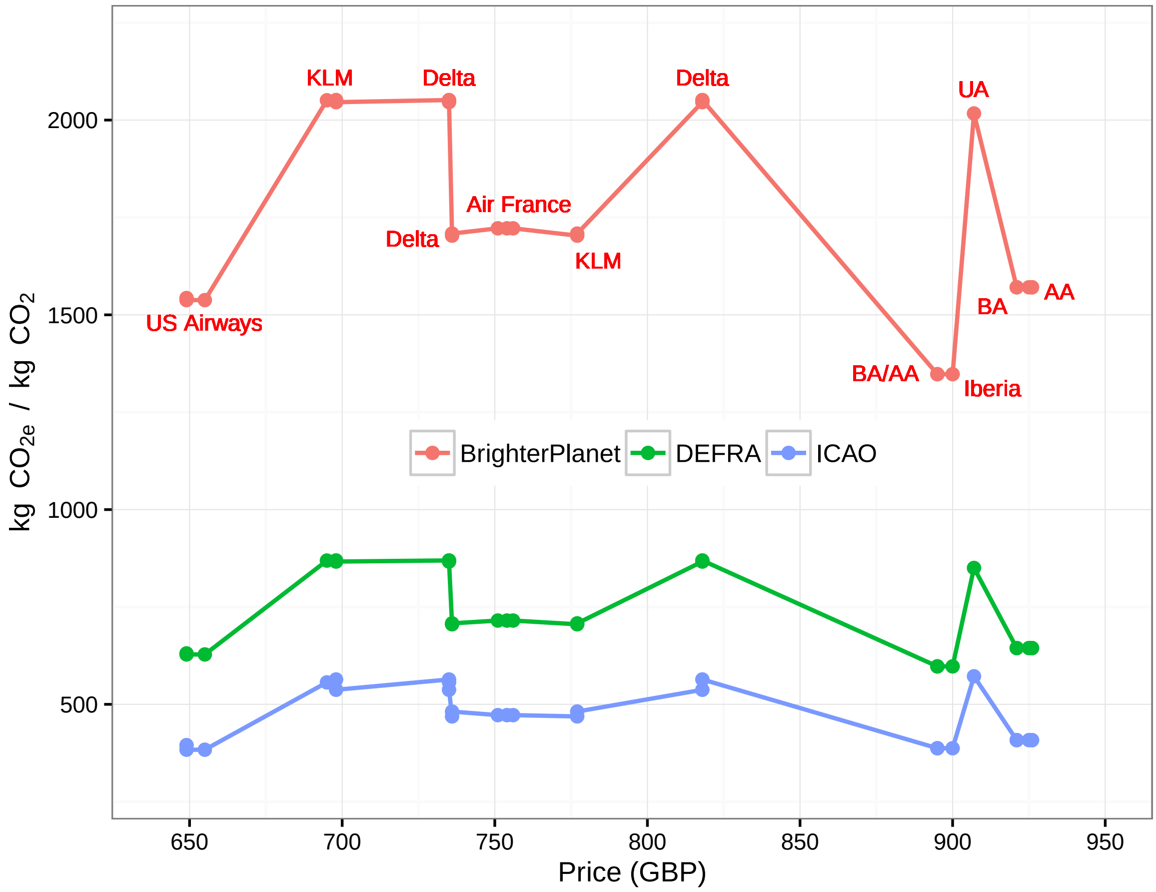


Figure 1: Manchester, UK, to New York (any airport); kg CO_{2e} on the vertical axis (kg CO_2 for ICAO), price (£) on the horizontal axis.

The estimates differ by factors ranging from 1.5 to 4.0. Nevertheless the estimates are nearly perfectly correlated with each other. All pairwise correlation coefficients are above 0.95. Regressing the carbon-emissions estimates on each other reveals nearly perfect linear relationships. For instance, regressing the ICAO estimate on the DEFRA estimate and a constant yields an adjusted coefficient of determination of 0.956 (see Table 1). Although statistically the intercept coefficient does not differ from zero, we retain this here and in subsequent regressions for consistency and comparability.

Table 1: MAN-NYC estimation results from regressing ICAO emissions on DEFRA emissions.

Regressand:[a] CO_2^{ICAO}					
Regressor[b]	Coefficient[c]	S.E.[d]	t^e	$P(>\|t\|)^f$	(95% C.I.)[g]
Constant	-0.185	19.99	-0.009	0.993	(-41.4, 41.0)
CO_{2e}^{DEFRA}	0.644	0.0272	23.7	0.000	(0.588, 0.700)
$R^2_{adj} = 0.956$, $F_{1,25} = 562.6$, $p < 0.001^h$					

[a]the left-hand-side, dependent variable
[b]the right-hand-side, independent variables
[c]estimated linear parameter on the independent variable
[d]standard error of the coefficient
[e]t-test statistic
[f]probability that t-test statistic exceeds its estimated (absolute) value
[g]95% confidence interval
[h]This row reports: (i) the percentage of variation in the dependent variable explained by the independent variables, adjusted for the number of parameters estimated (R^2_{adj}); (ii) the regression's F-test statistic on 1 and 25 degrees of freedom; and (iii) the probability of obtaining at least this F-test statistic value under the null hypothesis of no linear relationship.

The $CO_2^{ICAO} - \widehat{CO_2^{ICAO}}$ residuals are small, ranging from -21.05 to 25.46. The regression coefficient on CO_{2e}^{DEFRA} is statistically significantly different from both zero and one at the $\alpha = 0.05$ level (i.e. the 95% confidence interval excludes both zero and one). The significant F-test value reveals that the mean-only model is rejected in favor of the linear model. Regressions between the remaining method-pairs provide qualitatively comparable conclusions.

This nearly perfect collinearity implies that emissions calculated with these three methods contain essentially the same information and are indicative of each other. It suggests that whenever the absolute levels of emissions are not of primary interest – for instance when other considerations rule out non-air-travel modes – comparison of different flight options' GHG emissions is likely to lead to the same ranking with any one of the methods.

The consistency of the rankings generated by the ICAO, DEFRA, and BrighterPlanet methods may be investigated further using Kendall's coefficient of concordance W, which takes values between 0 and 1 and is related via simple transformation to both (i) the average of all bivariate Spearman rank-correlation coefficients ($\overline{r}$), and (ii) Friedman's non-parametric rank-sum test statistic. Kendall's W is a measure of inter-rater rank-order agreement. "It represents the ratio of the variability of the total ranks for the ranked entities to the maximum possible variability of the total ranks; a small ratio implies disagreement between judges" (Field, 2005). Being a non-parametric test, its validity is not predicated on any particular distributional assumptions. Table 2 presents both global and *a posteriori* tests of concordance between the ICAO, DEFRA, and BrighterPlanet methods using the sample of 27 MAN-NYC flights.[11] Globally, the three methods are almost-perfectly concordant ($W = 0.9819$). The null hypothesis that the three methods' rankings are independent is rejected by both the F test as well as the permutation-based χ^2 probability $p = 0.001$, which is guaranteed to be of correct size also on small samples (Legendre, 2005; Bonnini et al., 2014). Under the alternative hypothesis of the global test, at least one method is concordant with one or both of the remaining methods in this sample.

Table 2: Tests of concordance on MAN-NYC sample.

Global test				
Kendall's W	F	p-value	χ^2	p-value
0.9819	108.3	0.000	76.59	0.001

***A posteriori* tests**				
j Method	$\overline{r}_j$	W_j	p_j	p_j^H
1. CO_{2e}^{DEFRA}	0.9796	0.9864	0.0010	0.0030
2. CO_2^{ICAO}	0.9592	0.9728	0.0010	0.0030
3. CO_{2e}^{BrPl}	0.9796	0.9864	0.0010	0.0030

The *a posteriori* tests identify the individual contributions of the j methods to the global concordance statistic. Each $\overline{r}_j$ represents the mean of the bivariate Spearman rank-correlation coefficients between method j and the remaining methods. Accordingly, each partial concordance coefficient W_j represents the contribution of method j to the global concordance W. The final column reports p-values adjusted for multiple comparisons using the Holm method (p_j^H). In each *a posteriori* test, the null hypothesis is that method j is independent of the *all the remaining methods*. Hence finding that $p_j^H < \alpha = 0.05$ entails rejection of the null hypothesis, and we say that method j is concordant with all the remaining methods. In Table 2 all three Holm-corrected p-values are smaller than $\alpha = 0.05$, and thus each method is concordant with the other methods.

[11] See the kendall.global and kendall.post functions in the R package 'vegan', available from The Comprehensive R Archive Network (CRAN) at `cran.r-project.org/`.

4.2.2 Case 2: MAN-KUL

The results from different emissions calculation methods are not always highly correlated. For instance, the same analysis can be done on different flight options from Manchester, UK (MAN) to Kuala Lumpur, Malaysia (KUL). We restrict attention to economy flights of less than 24 hours duration departing between 7am and 10pm local time on May 1st 2013. Flights that involve more than three segments are excluded. Flights with prices above 1000GBP are excluded as well.

The price (on the horizontal axis) and carbon emissions (on the vertical axis) pairs for all the 29 available flights are plotted in Figure 2, where the emissions are calculated by BrighterPlanet, DEFRA, abd ICAO methods respectively.

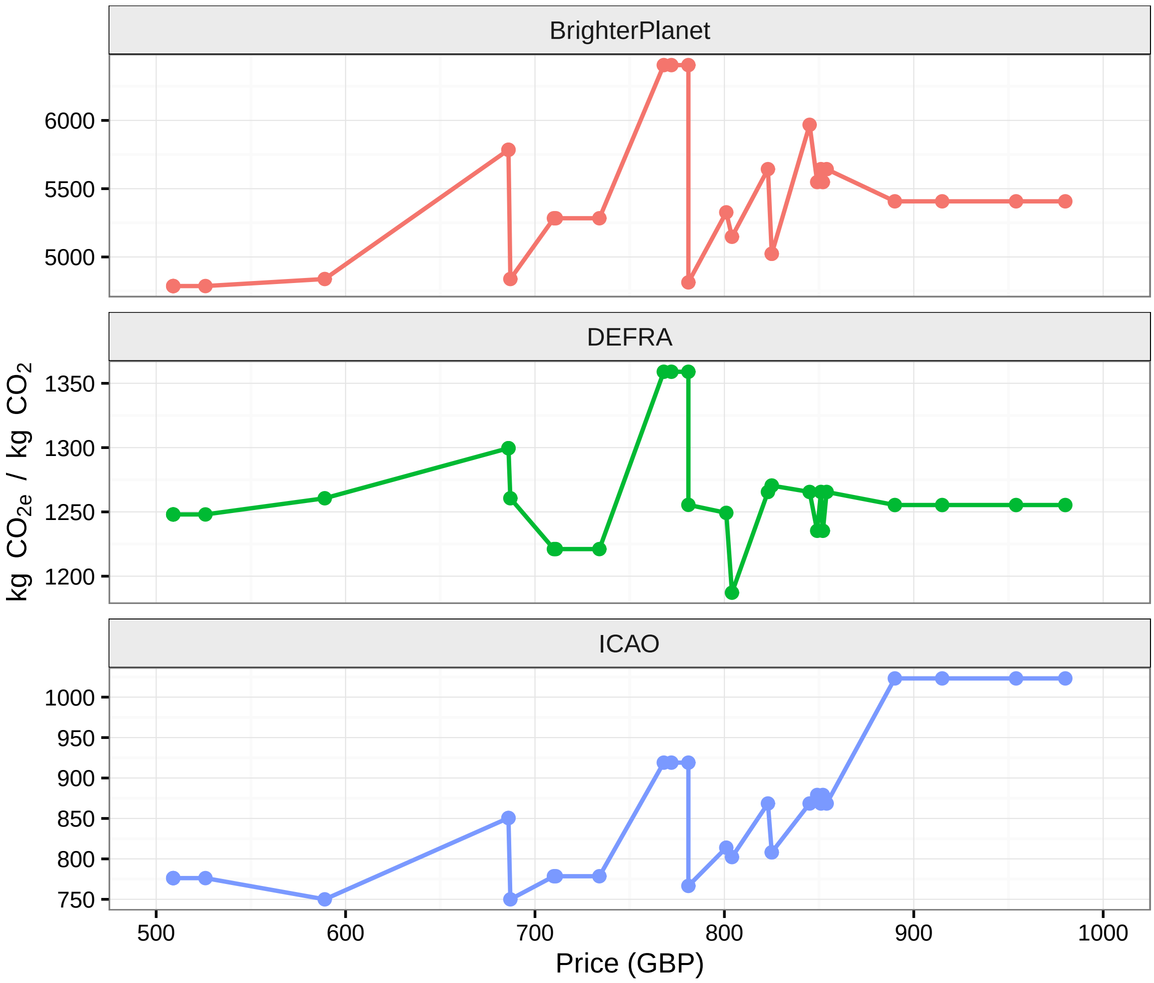


Figure 2: Manchester, UK, to Kuala Lumpur; kg CO_{2e} on the vertical axis (kg CO_2 for ICAO), price (£) on the horizontal axis.

It is clear that the between-method correlations are much weaker here than in the MAN–NYC sample.

Table 3: MAN-KUL estimation results from regressing ICAO emissions on DEFRA emissions

Regressand: CO_2^{ICAO}					
Regressor	Coefficient	S.E.	t	$P(>\|t\|)$	(95% C.I.)
Constant	-34.66	498.53	-0.07	0.945	(-1058, 988.2)
CO_{2e}^{DEFRA}	0.702	0.394	1.78	0.0863	(-0.1071, 1.511)
$R^2_{\text{adj}} = 0.0719,\ \ F_{1,27} = 3.17,\ \ p < 0.0863$					

Both the intercept and slope coefficients in Table 3 are statistically insignificant, and the coefficient of determination indicates very low explanatory power ($\mathrm{R}^2_{\text{adj}} = 0.0719$). The result is largely determined by the four flights with the highest prices, which show up as outliers in both residuals-vs.-fitted and quantile-quantile plots. For the four flights in this subset, the ICAO method generates high emissions estimates whilst both the DEFRA and BrighterPlanet methods yield only moderate emissions estimates. The ICAO result is influenced by a particularly low passenger load factor from Manchester to Helsinki and thus particularly high average passenger emissions on that leg. As a result, these four flights stand as outliers in the regression analysis and contaminate the linear regression result. (In what follows, we will accommodate this type of characteristic in the definition of a 'route-structure class'.) Excluding these four observations markedly improves both variance explained and statistical significance.

Table 4: MAN-KUL estimation results from regressing ICAO emissions on DEFRA emissions, excluding flights via Helsinki.

Regressand: CO_2^{ICAO}					
Regressor	Coefficient	S.E.	t	$P(>\|t\|)$	(95% C.I.)
Constant	-252.9	254.7	-0.993	0.331	(-779.8, 274.1)
CO_{2e}^{DEFRA}	0.852	0.201	4.23	0.000	(0.436, 1.27)
$R^2_{\text{adj}} = 0.414,\ \ F_{1,23} = 17.93,\ \ p < 0.001$					

However, in Table 4 the linear relationship between the ICAO estimate and the DEFRA estimate is still much weaker than that found in the previous section for MAN-NYC data. The reason may be that the flights from Manchester to New York fall into the same route-structure class: most share similar route-structure characteristics, consisting of a long-haul segment followed by a short-haul segment. Meanwhile, the flights from Manchester to Kuala Lumpur belong to different route-structure classes – they include a mixture of one-stop and two-stop flight options, and the structures of the flights differ considerably depending on the transfer airports. For instance, Manchester–London–Kuala Lumpur has very different characteristics from Manchester–London–Hong Kong–Kuala Lumpur, as the latter transfers once more than the former and hence consists of one long-haul segment between two short-haul segments. The Manchester–London–Kuala Lumpur route also has different characteristics from Manchester–Dubai–Kuala Lumpur, as the former has two unbalanced segments and the latter has two balanced segments.

Table 5: Tests of concordance on MAN-KUL sample, excluding flights via Helsinki.

Global test				
Kendall's W	F	p-value	χ^2	p-value
0.7657	6.535	0.000	55.13	0.001

A posteriori **tests**					
j	Method	$\overline{r}_j$	W_j	p_j	p_j^H
1.	CO_{2e}^{DEFRA}	0.5281	0.6854	0.0030	0.0030
2.	CO_2^{ICAO}	0.6876	0.7917	0.0010	0.0030
3.	CO_{2e}^{BrPl}	0.7297	0.8198	0.0010	0.0030

Although the three methods' global concordance is weaker on the MAN-KUL sample ($W = 0.7657$) than on the MAN-NYC sample ($W = 0.9819$), the hypothesis that the three methods' rankings are independent is rejected ($p = 0.001$); see Table 5. And on the *a posteriori* tests, $p_j^H < 0.05 \ \forall j = (1, 2, 3)$ so H_0 is rejected, whereby we infer that each method is concordant with the remaining methods.

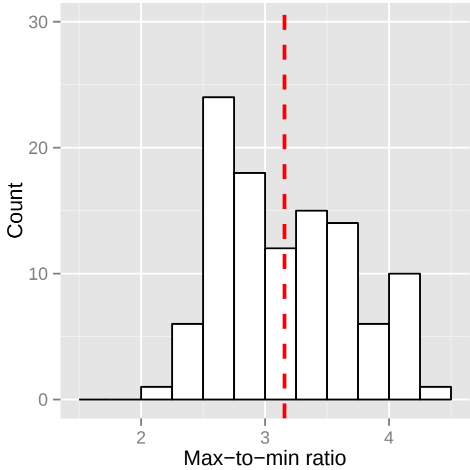
Since the complexity among various flight options will have different impacts on different emissions-calculation methods, in the following section we build two subsamples, each of which pools together flights that have different destinations but share common route-structure characteristics. Specifically, we propose the concept of a 'route-structure class' as a categorization criterion that takes into account the number of segments, the relative length of each segment (balanced/unbalanced) and passenger load factors. We test this concept below.

4.2.3 Case 3: WATS-based sample

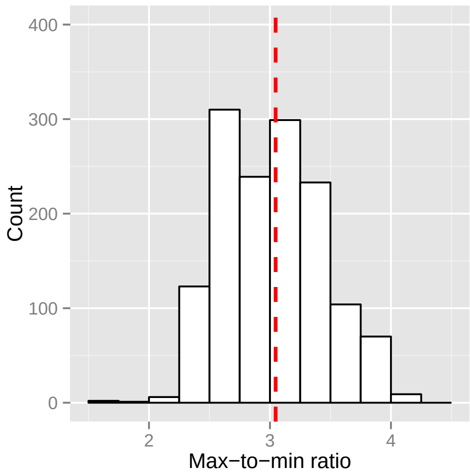
We seek a broader, representative, global sample for testing the rank equivalence of the emissions-calculation methods. Ideally this would entail compiling a frequency distribution of True-Origin–True-Destination (TO-TD) pairs and then sampling from this distribution. As it is based on ticketing data, IATA's PaxIS database allows the construction of such a TO-TD frequency distribution. However direct access to IATA's PaxIS database, even for purely academic research purposes, is prohibitively costly.[12] Hence we proceed to compile a sample that is broadly representative of the *highest-passenger-volume* TO-TD pairs using IATA's World Air Transport Statistics (WATS) digest of the PaxIS Plus data. The properties of the sample data and the procedures used to construct the sample are documented in Appendix A.

The WATS-based sample comprises $n = 107$ one-segment flights, $n = 1,403$ two-segment flights, and $n = 512$ three-segment flights. Below, we impose no further route-structure restrictions or requirements, such as on relative segment lengths or on passenger load factors. However, passenger load factors are in turn reflected – to differing degrees – in the DEFRA, ICAO and BrighterPlanet calculation methodologies. As the empirical results below show, the DEFRA, ICAO and BrighterPlanet methods deliver rank-order equivalence without the need to impose further route-structure restrictions.

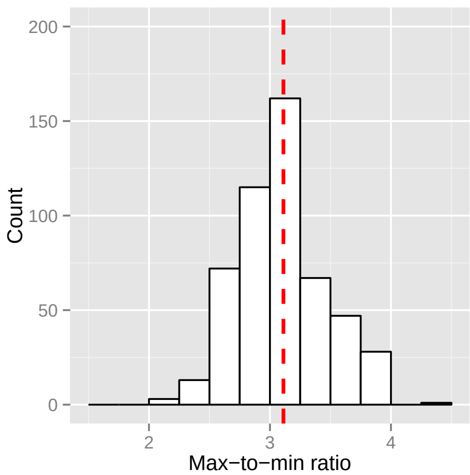
[12] The authors were quoted prices in range USD 50,000–60,000.



(a) One-segment flights ($n = 107$).



(b) Two-segment flights ($n = 1,403$). Seven outliers fall outside plot range.



(c) Three-segment flights ($n = 512$). Four outliers fall outside plot range.

Figure 3: Frequency distributions of max-to-min ratios.

We focus on how subsampling affects the result of regressing the ICAO emissions estimate on the DEFRA emissions estimate, and examine whether a clearer conclusion emerges. The first subsample contains flights with one segment, the second subsample contains flights with two segments, and the third subsample contains flights with three segments. Within the one-segment subsample the max-to-min ratio[13] ranges from 2.23 to 4.40. That is, the largest estimate (invariably BrighterPlanet) ranges between 223% and 440% of the smallest estimate. Within the two-segment subsample there are 7 outliers with a max-to-min ratio greater than 4.5. The remaining 99.5% of the two-segment subsample's max-to-min ratio falls between 1.55 and 4.5. And in the three-segment subsample the max-to-min ratio ranges from 1.43 to 4.5, with the largest of 4 outliers being 5.80. In all subsamples, both the mean and the median of the max-to-min ratio falls within the interval between 3 and 3.2. The associated frequency distributions are illustrated in Figure 3.

In the regression of CO_2^{ICAO} on CO_{2e}^{DEFRA} for the one-segment route-structure class, both the intercept and slope coefficients are statistically significant at the 0.1% level (see Table 6a). The 95% confidence interval for the slope coefficient excludes both zero and one; the slope is statistically significantly different from both one and zero. The linear relationship is very strong; the linear model as a whole performs statistically significantly better than the mean-only model ($F_{1,105} = 8177$, $p < 0.001$).

Table 6b presents the results of concordance tests on the one-segment route-structure class. In this subsample the three methods' global concordance is strong ($W = 0.991$), and the hypothesis that the three methods' rankings are independent is rejected ($p = 0.001$). On the *a posteriori* tests, $p_j^H < 0.05 \;\forall j = (1, 2, 3)$ whereby H_0 is rejected. We infer that each method is concordant with the remaining methods.

Precisely the same inferences emerge from the analyses of two-segment (Table 7) and three-segment (Table 8) subsample data. Thus, within each route-structure subsample, both linear association and concordance of rankings are strong and statistically significant.

[13] specific to each flight: the maximum GHG emission estimate divided by the minimum GHG emission estimate

Table 6: Estimation results for the one-segment route-structure class subsample (107 distinct flights).

(a) Regression.

Regressand: CO_2^{ICAO}					
Regressor	Coefficient	S.E.	t	$P(>\|t\|)$	(95% C.I.)
Constant	47.1	3.05	15.4	0.000	(41.07, 53.17)
CO_{2e}^{DEFRA}	0.591	0.00654	90.4	0.000	(0.5781, 0.6041)
$R^2_{\text{adj}} = 0.9872,\ \ F_{1,105} = 8,177,\ \ p < 0.001$					

(b) Tests of concordance.

Global test				
Kendall's W	F	p-value	χ^2	p-value
0.991	213.4	0.000	315.0	0.001

***A posteriori* tests**					
j	Method	$\overline{r}_j$	W_j	p_j	p_j^H
1.	CO_{2e}^{DEFRA}	0.9885	0.9924	0.0010	0.0030
2.	CO_2^{ICAO}	0.9803	0.9869	0.0010	0.0030
3.	CO_{2e}^{BrPl}	0.9893	0.9929	0.0010	0.0030

5 Conclusion

To summarize, we have found strong linear correlations between different GHG emission-calculation methods when the flights included in the sample belong to a common route-structure class.

As long as the relevant set of flight options falls within the same route-structure class, analysis based on any one of the emissions-calculation methods will generally lead to the same GHG-footprint ranking – which is precisely the information needed to make environmentally responsible decisions at the point of purchase.

This partial resolution of emissions-estimate confusion suggests relative rankings as an informationally sufficient and pragmatically implementable way forward to allow identification of the least-harmful flight from among those within a particular route-structure class. Front-page, point-of-choice display of within-class rankings is implementable, valid, and avoids multiple-methods, multiple-estimates ambiguity. But where the travel mode is not restricted by external

Table 7: Estimation results for the two-segment route-structure class subsample (1,403 distinct flights).

(a) Regression.

Regressand: CO_2^{ICAO}					
Regressor	Coefficient	S.E.	t	$P(>\|t\|)$	(95% C.I.)
Constant	96.2	1.72	55.9	0.000	(92.86, 99.61)
CO_{2e}^{DEFRA}	0.586	0.00215	273	0.000	(0.5816, 0.5901)
$R^2_{\text{adj}} = 0.9815$, $F_{1,1401} = 74,320$, $p < 0.001$					

(b) Tests of concordance.

Global test				
Kendall's W	F	p-value	χ^2	p-value
0.993	279.1	0.000	4176	0.001

***A posteriori* tests**				
j Method	$\overline{r}_j$	W_j	p_j	p_j^H
1. CO_{2e}^{DEFRA}	0.9915	0.9944	0.0010	0.0030
2. CO_2^{ICAO}	0.9870	0.9912	0.0010	0.0030
3. CO_{2e}^{BrPl}	0.9896	0.9931	0.0010	0.0030

considerations, there is no substitute for direct comparison of emissions levels – with all the attendant ambiguity and credibility problems.

Nevertheless, the precise manner in which relative ranking information should be presented remains an open question. The study of choice architecture is rapidly growing due to ample evidence – amassed within psychology, behavioral economics and interface design – that information *presentation format* impacts upon choice behavior as much, if not more, than the mere presentation of information itself (Johnson et al., 2012). In transport choice, the framing of information affects choice behavior (Avineri and Waygood, 2013), as do social comparisons (Gaker et al., 2010). Accordingly, the present results suggest the incorporation of relative CO_{2e}-ranking information into flight-choice interface design and into the supporting choice-architecture research.

Finally, our results leave unanswered how one should rank flight-search results containing a

Table 8: Estimation results for the three-segment route-structure class subsample (512 distinct flights).

(a) Regression.

Regressand: CO_2^{ICAO}					
Regressor	Coefficient	S.E.	t	$P(>\|t\|)$	(95% C.I.)
Constant	115.4	4.09	28.2	0.000	(107.4, 123.5)
CO_{2e}^{DEFRA}	0.603	0.00352	171	0.000	(0.5960, 0.6098)
$R^2_{adj} = 0.9829,\ F_{1,510} = 29,370,\ p < 0.001$					

(b) Tests of concordance.

Global test				
Kendall's W	F	p-value	χ^2	p-value
0.992	257.1	0.000	1521	0.001

***A posteriori* tests**					
j	Method	$\overline{r}_j$	W_j	p_j	p_j^H
1.	CO_{2e}^{DEFRA}	0.9906	0.9937	0.0010	0.0030
2.	CO_2^{ICAO}	0.9875	0.9917	0.0010	0.0030
3.	CO_{2e}^{BrPl}	0.9872	0.9914	0.0010	0.0030

mixture of two or more route-structure classes. Purely technical or statistical means do not exist for extending a ranking across different route-structure classes. It is conceivable, however, that a majority-ranking algorithm could serve this purpose. We leave the substantial undertaking of developing and rigorously validating such an algorithm for future work.

Acknowledgements

This research was supported by Research Councils UK under research grant number EP/I00033X/1. The authors wish to thank Adrian Friday, Paul Peeters, the Editor, and three anonymous TRD reviewers, for constructive comments. The usual disclaimer applies.

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Appendices

A Construction of the WATS-based sample

Step 1. In constructing the sample of flights for analysis in Case 3 we make use of IATA's 'World Air Transport Statistics' (WATS) report (IATA, 2014). The WATS report describes its coverage and inclusion as follows.

> The top city-pair rankings presented in this section have been sourced from IATA's PaxIS Plus. Passenger volumes are based on the origin and destination of the passenger's itineraries, which may have included intermediate connections. The coverage is total scheduled traffic, including IATA members as well as non-members. All city-pair rankings in this section consider inbound and outbound passengers, and consolidate commercial airports with a metropolitan area. (IATA, 2014)

Overall, we obtain a sample of 54 top passenger city pairs. For each of the following route areas, we select the three top passenger city pairs: Asia – Southwest Pacific, Europe – Far East, Europe – Middle East, within the Far East, the Mid and South Atlantic, Middle East – Far East, North Atlantic, North America – Latin America/Caribbean, North and Mid Pacific, Europe – Southern Africa, Within Europe, China, Japan and USA. One top passenger city pair is chosen for each of 12 route areas including Australia, Brazil, India, Korea, Russia, Africa – Middle East, Europe – Northern Africa, Europe – Southwest Pacific, within the Middle East, within North America, within South America and within the Southwest Pacific.

Step 2. Based on these 54 city-pairs, we collect all flight-route options utilizing Skyscanner's consolidated search engine.[14] For each of the city-pairs, it is assumed that a passenger is to arrange a single flight from the origin city to the destination city on 01/09/2015. To follow the WATS report, we also consolidate commercial airports with a metropolitan area. All flight-route options with 3 or fewer legs are recorded for each city-pair, including the information of departing airport, arrival airport and transfer airport(s) for flight routes with 2 or 3 legs.

Step 3. Then all the flight routes are pooled together and divided into three subsamples: flight routes with 1 leg, 2 legs and 3 legs respectively.

[14] `www.skyscanner.net`

Step 4. For each flight-route option, we query the ICAO carbon emission calculator[15] for flight distance (GCD) and emissions for each leg.[16] DEFRA emissions for each leg can be calculated by applying a multiplier to the flight distance. BrighterPlanet emissions for each leg can be collected from the BrighterPlanet API.[17].

[15] `http://www.icao.int/environmental-protection/CarbonOffset/Pages/default.aspx`

[16] Flights for which the emissions figure is missing in the ICAO database are subsequently excluded before the analysis is conducted.

[17] `www.brighterplanet.com`

Highlights

- GHG emissions estimates vary greatly, depending on the calculation method employed
- the strictest method's estimate is up to 4.5 times larger than the most conservative
- this heterogeneity prevents industry from displaying CO_{2e} at the point of choice
- we show that different calculation methods yield consistent *rank* orderings
- point-of-choice display of flights' CO_{2e} ranking suffices for emissions-minimizing choice