# MODELLING AIRLINE COST PASS-THROUGH WITHIN REGIONAL AVIATION MARKETS

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Word count: 6,234 words text + 5 tables/figures x 250 words (each) = 7,484 words

TRR Paper number: 18-04368

Submission Date: 13th March 2018

**ABSTRACT**

Studies assessing the impact of market-based environmental policies in aviation rely on various scenarios of airline cost pass-through, because there is little empirical evidence with respect to the impacts of airline costs on airfares. Instead, the costs effect has been indirectly measured by proxy variables such as distance, fuel price, and aircraft sizes. This paper provides empirical evidence of airline cost pass-through by developing an airfare model that explicitly captures airline operating costs. Using a feasible generalized two-stage least squares (FG2SLS) approach, we obtained coefficients of airline fuel costs per passenger, non-fuel costs per passenger, and non-fuel costs per flight modelling for 7 world regions (20 region-pair markets). A comparison of the estimated cost pass-through elasticities conducted across regional markets suggests that airlines may respond to the costs increases differently, depending on the costs type and the market they operate in. Based on the estimated coefficients, we systematically evaluate the potential impacts of introducing a carbon tax policy within two major regional markets with distinct cost pass-through elasticities.

*Keywords*: airline cost pass-through, emissions reduction, regional aviation markets

## INTRODUCTION

To achieve carbon-neutral growth in international aviation, the International Civil Aviation Organization (ICAO) has introduced a Market-based Measures (MBMs) scheme. The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), which is planned to be introduced in 2021, will effectively increase the airlines' fuel costs *(1)*. Airlines will respond to the higher fuel costs by adjusting technology, operations, and air fares. However, higher fares in a competitive market may result in – depending on the elasticity of demand relative to supply – lower sales and market shares. Therefore, an airline has to strike a balance between recovering costs increases and maintaining its market share. Cost pass-through rates will manifest this balance. Additionally, as airline operating costs consist of several components, an airline could potentially be more vulnerable to changes in one cost component than the other. For example, an increase in fuel costs may have greater impacts to airlines than a same increase in aircraft landing costs. Thus, it would be interesting to assess the potential pricing responses of airlines to changes in different operating costs under competition.

Cost pass-through can be measured either by the absolute price increase resulting from an absolute increase of costs, known as the absolute cost pass-through, or by the percentage change in price for a percentage change in marginal cost, known as the cost pass-through elasticity *(2)*. Using either measure, previous empirical studies have mainly assessed cost pass-through in the oil industry, the wholesale electricity industry, and the exchange rates to import prices, etc. *(2)*. However, there is little empirical evidence with respect to airline cost pass-through *(3)*, and thus the economic impacts of MBMs on airline pricing behavior remains largely unclear. As a result, most of the studies that aim to assess the extent to which MBMs could lead to aviation emissions reduction had to assume rates of cost pass-through. For instance, both Anger and Kohler *(4)* and Scheelhaase *et al. (5)* assumed that the allowance cost of the European Emissions Trading Scheme (EU ETS) would be fully passed onto passengers and concluded that increases in airfares would be small because of a low carbon price. In evaluating impacts of the EU ETS on airline networks, Albers *et al.* used two scenarios of 35% and 100% cost pass-through *(6)*. Similarly, Meleo, *et al.* assumed three cost pass-through scenarios: 0%, 50%, and 100%, in their study on the direct costs increases in the Italian airline market *(7)*. The widely-adopted scenario-based cost pass-through in previous research suggests that a solid understanding of the behavior change in airline pricing is at the heart of evaluating economic impacts of MBMs on the aviation sector. Therefore, more empirical research is needed on this subject.

Estimating the cost pass-through requires estimating airfares in a competitive environment. How airlines set fares has been studied extensively, albeit with a focus on the U.S. domestic airline market. Existing literature has found several factors that affect airfares.

Passenger demand was found to be positively correlated with fares, if the demand impact outweighs the economies of density effect *(8, 9)*, and negatively correlated otherwise *(10)*. Airline competition also has significant impacts on airfares, and has thus far received the most extensive discussion in literature, since the deregulation of the airline industry in the U.S. in 1978 *(11, 12)*. Studies discovered that after the deregulation, airlines with market power tend to charge higher fares *(8, 13, 14)*. In these studies, market structure has been measured by the level of market concentration using the Herfindahl-Hirschman Index (HHI). Higher market concentration indicates relatively low competition, and vice versa. Another critical indicator of market competition is the presence of low-cost carriers (LCCs). Fares are found drastically depressed if a LCC enters a market *(15, 16)*. And Brueckner, *et al.* further demonstrated that the presence of LCCs will affect airfares in not only local airport-pair markets but also neighboring markets *(17)*.

Studies have also found significant yet inconclusive impacts of flight delays on airfares. Forbes showed that every one-minute increase in delay leads to a $1.42 reduction in fares *(18)*.

In contrast, Zou and Hansen, who estimated the delay effects separately for non-stop and one-stop routes, concluded that delays will result in higher fares *(10)*. Although flight frequency is relatively less often included in previous fare models, it also has significant effects on prices. According to Chi and Koo, higher flight frequencies could result in either higher or lower fares, depending on if the effect of greater frequency on costs is larger than its effect on demand *(19)*. Finally, although the impact of operating costs on airfares has been widely acknowledged, few studies modelled airline operating costs explicitly. Instead, in most cases, distance, fuel price, and aircraft sizes have been used as proxy variables of airline costs. If controlling for demand, frequency, and competition effects, then longer O-D distance, higher fuel price, and larger aircraft are associated with higher fares *(8, 10, 19)*. However, these proxy variables cannot capture changes in specific airline costs, and thus are not useful to quantify how much of airline's costs burden is passed through to passengers via airfares, which is the focus of this research.

Based on this literature review, this paper aims to empirically evaluate airline cost pass-through for 7 world regions (20 region-pair markets) and to compare the pass-through elasticities across different airline markets. An airfare model that explicitly captures airline operating costs as well as other key influencing factors is developed and estimated for each of these regional markets.

Our research makes several contributions. First, we provide empirical evidence on airline cost pass-through to future research that otherwise would have to rely on presumed cost pass-through rates when evaluating the economic impacts of MBMs on the aviation sector. Secondly, having estimated the fare model at a global scale, our results have implications to both developed and developing airline markets. This is particularly important to regions beyond the U.S. domestic market, where aviation emissions are projected to grow more rapidly over the next 20-30 years *(20)* yet have not been explored in the current body of airline pricing studies. Finally, coefficients estimated from our model could be used to evaluate potential impacts of MBMs such as CORSIA on airline pricing behavior, but also to help policy makers to design other aviation emissions reduction policies. Notably, our airfare model is a core component of the updated Aviation Integrated Model AIM2015 *(21)*.

The next section of this paper describes the data underlying this work, the model specification, and the three key operating cost variables, namely fuel costs per passenger, non-fuel costs per passenger, and non-fuel costs per flight. The model estimation and estimated coefficients are then discussed in Section 3. Based on the coefficient estimates, a carbon tax policy scenario is evaluated within two regional markets with distinct cost pass-through elasticities. Using the AIM2015 Model, the scenario analysis compares the system-wide impacts of increased airline costs on airfare, demand, and aviation $CO_2$ emissions. Section 4 offers conclusions.

## DATA AND EMPIRICAL MODEL

This section presents the airfare model developed in this research. We first describe the datasets used to construct the model variables. The specification of the model then follows and we conclude with a detailed discussion of the three key operating-costs variables.

### Data

Data describing airfares, passenger demand, market shares, flight frequency, and route characteristics are either directly obtained, or constructed from the Sabre Market Intelligence database *(22)*. Fleet data is obtained from FlightGlobal and is used to derive aircraft type by segment *(23)*. Aircraft are grouped into nine different size classes, based on the Sustainable Aviation aircraft categories *(24)*. En-route and airport landing charges by size class are provided by the RDC airport charges database *(25)*.

Our fare model uses cross-sectional data for the year 2015, with itineraries connecting different Origin-Destination (O-D) region-pairs grouped into intra-regional markets (e.g. Europe-Europe) and inter-regional markets (e.g. North America-Europe). We weighted airfares (including taxes) by the number of passengers paying different observed prices based on booking classes, and aggregated ticket prices of all airlines operating on the same route as the annual weighted average price. The unit of observation is a unique route between an O-D airport-pair, connected by a maximum four flight segments. To ensure a robust model estimation, routes with very low demand are removed. We restrict low-traffic routes to those with a share of the total O-D passengers on a given city-pair below 5%, and annual passengers fewer than 52 (1 passenger per week) in intra-regional markets or 520 (10 passengers per week) in inter-regional markets.

Figure 1 describes four key aspects of the cleaned data. Our data covers all continents over the world (a). The largest five markets in terms of RPK are AP-AP, NA-NA, EU-EU, AP-EU, and AP-NA, and the top 20 region-pair markets out of 28 account for 90% of the global total RPK (b). The share of RPK is closely linked to the total number of airports available in each region (c). As 78% of the global airports are located in AP, NA, and EU, markets connecting these regions account for the largest proportion of the global RPK. Finally, from (d) we can see that overall fares are higher in inter-regional markets than in intra-markets (also with greater variation in fares), and the highest average fares are found in those smallest markets potentially because of the limited supply.

**Model Specification**

Informed by the literature reviewed earlier, we formulate fare as a function of several factors that have demonstrated significant pricing impacts. These factors are grouped in an overview equation in Eq.(1) as *Cost*, *Demand*, *Competition*, and *O-D Country Fixed Effects*, where *m, k, n* are origin, connecting, and destination airport(s), respectively:

$$(Fare)_{mkn} = f(Cost_{mkn}, Demand_{mkn}, Competition_{mkn}, CountryFE_{OD}) \tag{1}$$

Fares are determined by the complex interactions between supply and demand, where supply is expressed mainly via airline costs (but also flight frequency). Competition which not only often acts as the equilibrium-shifter but also has significant influence on airline cost pass-through *(3)* is included. The unobserved effects of endpoint countries that may affect airline pricing differently (e.g. taxes on fares) are captured by country fixed effects. Following this rationale, the airfare model is specified in Eq.(2) as follow:

$$\begin{aligned}\ln(Fare)_{mkn} = {} & \beta_0 + \beta_1 \ln(FuelCostPerPax)_{mkn} + \beta_2 \ln(NonFuelCostPerPax)_{mkn} \\ & + \beta_3 \ln(NonFuelCostPerFlt)_{mkn} + \beta_4 \ln(Freq)_{mkn} + \beta_5 \ln(Pax)_{mkn} \\ & + \beta_6 \ln(RouteShare)_{mkn} + \beta_7 \ln(CUIMean)_{mkn} + \beta_8 \ln(LegMeanHHI)_{mkn} \\ & + \beta_9 \ln(AirportMeanHHI)_{mkn} + \beta_{10}(Nlegs)_{mkn} + \beta_{11}(HubsPass)_{mkn} \\ & + \sum_{O=2,3,4\ldots} \delta_O OriginCountry_O + \sum_{D=2,3,4\ldots} \theta_D DestCountry_D + \varepsilon_{mkn}\end{aligned} \tag{2}$$

where *m, n,* and *k* denote origin-, destination-, and connecting airport(s), respectively; $O$ and $D$ denote origin country and destination country, and $\varepsilon$ is the random error. Definition of the fare model variables are provided in Table 1. As mentioned earlier, the costs pass-through can be measured by either the absolute pass-through rate or the pass-through elasticity. In this study, we measure the pass-through by elasticity using a log-log model specification, which allows us to compare the percentage changes of airfares given a same percentage of increase in different costs types. Notably, we do not include any dummy variable for LCC, as they mainly operate in limited markets (e.g. U.S. and EU). Therefore, including this variable does not significantly improve the model performance when estimate other world regions.

**Airline Operating Costs Variables**

As discussed in literature review, airline operating costs have been largely measured by proxy variables such as distance, fuel price, and dummy variables for aircraft sizes in previous airfare models *(8, 10, 19)*. Such proxy variables cannot directly quantify the effects of changes in airline costs to airfares. In contrast, this fare model includes three operating costs variables that have this capacity. As shown in Figure 2 we firstly categorized all flights on a flight segment into 9 aircraft size classes based on the Sustainable Aviation categories *(24)*. Each aircraft size class is associated with 7 different operating costs components, which are either calculated by the AIM2015 Direct Operating Cost (DOC) Model *(25)* or derived from the RDC airport charges database *(26)* as input to calculate total operating costs of all flights on a given segment.

The 7 operating costs components are grouped into three categories, i.e. fuel costs, non-fuel passenger costs, and non-fuel flight costs. Fuel costs and non-fuel costs are distinguished because fuel costs is generally the single largest costs component that has shown great fluctuations over the past 15 years *(3)*, whereas other costs components are relatively stable over time. Thus, fuel costs is the main source of volatility in airline total costs and needs to be measured separately. Additionally, fuel costs and non-fuel passenger costs are divided by passenger demand as costs per passenger because their total segment costs are determined by the enplaned passenger numbers. For instance, fuel costs of a full flight will certainly be higher than that of a same-size empty flight due to heavier weight. In contrast, non-fuel flight costs is averaged by flight frequency because each aircraft's flight-based costs (Figure 2) is fixed and does not change with the number of enplaned passengers. Eq.(3) to Eq.(5) show how the three costs variables are derived as follow:

$$(FuelCostPerPax)_{mkn} = \sum_{l\in Legs} \frac{\sum_{f,l} FuelC_{f,l}\, Freq_{f,l}}{Pax_l} \quad \forall Legs \in mkn \tag{3}$$

$$(NonFuelCostPerPax)_{mkn} = \sum_{l\in Legs} \frac{\sum_{f,l} (PaxLndC + VolC)_{f,l}\, Pax_{f,l}}{Pax_l} \quad \forall Legs \in mkn \tag{4}$$

$$(NonFuelCostPerFlt)_{mkn} = \sum_{l\in Legs} \frac{\sum_{f,l} (FltLndC + CrewC + MtnC + OwnC)_{f,l}\, Freq_{f,l}}{Freq_l} \quad \forall Legs \in mkn \tag{5}$$

In Eq.(3), $FuelC_{f,l}$ represents the fuel costs of an aircraft in size class $f$ flying on segment $l$, and $Freq_{f,l}$ denotes the annual total flight frequency of aircraft in this size class on segment $l$. The total fuel costs of all aircraft on the segment $l$ are then averaged by the annual total passengers of this segment ($Pax_l$). Finally, the fuel costs per passenger on itinerary *mkn* is the sum of fuel costs per passenger of all segments (*Legs*) on *mkn*.

Similarly, in Eq.(4), $(PaxLanC + VolC)_{f,l}$ is the total non-fuel passenger costs associated with one passenger, i.e. passenger landing charges and volume-related costs (Figure 2) on aircraft size $f$ flying over segment $l$; and $Pax_{f,l}$ is the annual total passengers on aircraft size $f$ and segment $l$. Lastly, in Eq.(5) the non-fuel flight costs is the sum of flight landing charges (*FltLandC*), crew costs (*CrewC*), maintenance costs (*MtnC*), and ownership costs (*OwnC*) (Figure 2) for aircraft size $f$ and on segment $l$. The segment total non-fuel flight costs is averaged by total flight frequency over all size classes on segment $l$ ($Freq_l$).

## MODEL ESTIMATION RESULTS AND DISCUSSION

In this section, the model estimation is briefly described, followed by interpretation and discussion of the coefficients of the three costs variables estimated from the world's top 20 region-pair markets. We conclude with an analysis of the system-wide impacts of introducing a carbon tax in two regional markets with distinct cost pass-through elasticities on demand, fares, and $CO_2$ emissions, using the AIM2015 model.

**Model Estimation**

Airfare models are complicated by the endogeneity bias arising from the demand effects from fares, i.e. a change in demand by a change in airfares. From Eq.(2), this potentially affects five right-hand side variables, namely Pax, RouteShare, Freq, LegMeanHHI, and AirportMeanHHI. The number of O-D passengers on a given route is clearly endogenous as changes in fares also affect passenger demand. RouteShare, defined as the share of total O-D passengers on this city-pair using a given route, may be endogenous because it is a function of O-D demand (Pax). Similarly, HHIs are also potentially endogenous, given that airline's market share, which is input to calculate HHIs, is expected to be a function of the price it charges *(13, 19)*. Flight frequency may be endogenous because increases in frequency will have lower per-flight costs, thus lowering fares, which in turn attract more demand, resulting in a change in frequency. After conducting the traditional Breusch-Pagan test *(27)* and the Hausman test *(28)*, we found that the null hypotheses of homoscedasticity and exogeneity can be rejected at the 0.1% level in this model, indicating that heteroskedasticity exists and the five variables are endogenous.

To correct for the endogeneity and heteroskedasticity bias, we estimate the model using a feasible generalized two-stage least squares (FG2SLS) procedure, with lagged Pax, RouteShare, LegMeanHHI, AirportMeanHHI and Freq in year 2014 as instrumental variables (IVs). The estimation procedures are: (1) estimate OLS residuals from the reduced-form equation; (2) regress the log of the squared residuals over all the exogenous variables (including the IVs); (3) estimate the error variance from the fitted values in step (2); (4) apply 2SLS with the dependent variable, the explanatory variables, with all the IVs divided by the estimated error variance *(29, 30)*.

**Results and Discussion**

Because of the space constraints, Table 2 reports the coefficients of only the three key operating costs variables estimated from the top 20 regional-pair markets, which account for 90% of the global RPK (Figure 1. (b)). Overall, out of the 60 coefficient estimates across the 20 airline markets, only 10 are not statistically significant. The other 50 estimated coefficients have high statistical significance at least at the 1% level, and all have the expected positive signs. This demonstrates that airlines do pass increases in fuel costs, non-fuel passenger costs, and non-fuel flight costs onto passengers through higher airfares.

Importantly, the coefficients tend to vary in magnitude, depending on the specific type of costs that airlines pass through and the particular regional market in which they operate. Additionally, we found fairly large values for the first stage $F$-statistics of the added IVs, suggesting that the chosen IVs are sufficiently strong. The adjusted $R^2$ values range from 0.520 to 0.938, indicating that our model explains a significant proportion of the variance in airfares of the 20 markets. Next, the cost pass-through elasticities for each costs type will be interpreted and discussed for intra- and inter-regional markets, respectively.

Among the 7 intra-regional markets, 6 coefficients prove to be statistically significant for the fuel costs variable at the 0.1% level. Airlines in AP-AP are the most responsive to changes in fuel costs, with an elasticity between 0.36 and 0.39. The relatively high elasticity in AP-AP can be explained by the fact that fuel costs account for a larger share of total airline costs, due to a wider geographical coverage (i.e., ranging from Russia to Australia), compared to other intra-markets. This follows by SA-SA (0.20-0.28), EU-EU (0.23-0.25), and AF-AF (0.20-0.27), which have very close pass-through elasticities within 95% confidence intervals. NA-NA is slightly less elastic to fuel costs changes. For every 10% increases in fuel costs, fares in NA-NA will increase by 1.9-2.1%. The elasticity with statistical significance is the lowest in CA-CA (0.14-0.20), which shows only about half of the fuel-costs effects compared to AP-AP (0.36-0.39). The only statistically insignificant coefficient is found in ME-ME, suggesting that increases in fuel costs do not have an airfare impact in ME-ME. This can be attributed to the fact that the majority of routes in ME-ME are operated by Gulf national flag carriers that have considerably cheaper fuel costs due to the region's proximity to oil production and refining facilities leading to lower supply chain costs (*31*).

All seven estimates for the non-fuel flight costs are statistically significant at the 0.1% level. Sharply contrasting with the result from the fuel costs estimation, ME-ME is found to be the most responsive to changes in non-fuel flight costs. For each 10% increases in this costs, the mean of fares in ME-ME will increase by 5.5-7.7%. Once again, this result demonstrates that with the fuel costs considerably cheaper, airlines in the ME-involved markets are the most vulnerable to changes in the other big component of airline operating costs, i.e. the flight-based costs. In contrast, NA-NA and EU-EU are the least elastic to nonfuel flight costs changes, with the estimated coefficients both between 0.15 and 0.16. Between the highest and the lowest elasticities, SA-SA ranks the second most elastic market yet only has an elasticity (0.32-0.40) slightly more than half of that of ME-ME; elasticities of the third to the fifth markets are AF-AF (0.24-0.30), AP-AP (0.20-0.23), and CA-CA (0.14-0.19), respectively.

Five out of seven intra-markets for the non-fuel passenger costs have statistically significant estimates, with ME-ME and CA-CA as exceptions. SA-SA, which has been found the second most elastic market to changes in both fuel and non-fuel flight costs, proves to be the most sensitive market to this costs type (0.48-0.68). This follows by AF-AF having a pass-through elasticity between 0.20 and 0.36 within 95% confidence intervals. Coefficients of AP-AP (0.13-0.18) and NA-NA (0.14-0.17) are not statistically significantly different within 95% confidence intervals. EU-EU has the lowest elasticity with statistical significance, with every 10% increase in non-fuel per passenger costs leading to only 0.6-0.8% fare increase.

We now turn to the coefficients of the 13 selected inter-regional markets. Given that the inter-regional markets connect two different O-D regional markets with distinct characteristics, the estimated cost pass-through elasticities could provide additional insights.

Out of 13 estimates for the fuel costs variable, 10 have statistically significant coefficients at the 0.1% level. The three statistically insignificant coefficients all concern the ME-involved markets, namely AP-ME, NA-ME, and AF-ME. This is similar to our findings in the intra-markets estimates, and again demonstrates that the ME-involved markets are generally unaffected by fuel costs increases. Out of the 10 statistically significant estimates, AP-EU is the most sensitive inter-regional market to fuel costs, whose estimated pass-through elasticity is about 0.31-0.37. EU-SA follows closely with an estimated coefficient between 0.25 and 0.39 within 95% confidence intervals. Two groups of markets are found to have very close elasticities. One group contains CA-NA (0.21-0.25) and EU-NA (0.18-0.25), and the other group includes NA-SA (0.12-0.24), AP-NA (0.11-0.21), AF-EU (0.11-0.19), and CA-EU (0.08-0.20). The least elastic markets to fuel costs changes are EU-ME (0.07-0.17) and AF-AP (0.01-0.10).

Similar to the results found in the intra-regional markets, the non-fuel flight costs' coefficients of all 13 inter-regional markets are statistically significant at the 0.1% level. This finding provides an important implication that policy interventions in increasing non-fuel flight costs will have the most widespread significant effects to airline pricing behavior globally. Nevertheless, the effects still differ significantly in magnitude between the 13 markets. Consistent with our findings from the intra-markets coefficients, the ME-involved markets are the most responsive to the non-fuel flight costs changes. Out of the top four markets with the highest elasticities to this costs type, three are the ME-involved markets. In particular, average fares in AF-ME will increase by 3.6-4.5% as a result of a 10% increase in non-fuel per flight costs. AF-AP follows closely after AF-ME with an elasticity between 0.33 and 0.41. EU-ME and NA-ME have slightly lower coefficients at 0.29-0.38 and 0.20-0.45, respectively. In addition, coefficients of CA-EU, NA-SA, AP-NA, AP-ME, and AF-EU all range from 0.20 and 0.35 within 95% confident intervals. Market with the lowest elasticity to this cost type is CA-NA, i.e. with 10% increases in the per flight costs, fares will only increase by 0.6-0.9%.

Lastly, 4 out of 13 coefficients for the non-fuel per passenger costs are statistically insignificant. Together with the two statistically insignificant coefficients found in the intra-market results, this costs type has 6 out of the 10 statistically insignificant estimates across all the 60 estimated coefficients. In addition, the values of cost pass-through elasticities of the non-fuel per passenger costs are overall smaller than those of the other two operating costs categories. For instance, AP-NA has the highest elasticity but only at 0.23-0.28, which is significantly lower than the most fuel costs-sensitive inter-market AP-EU (0.31-0.37) and the most flight costs-sensitive market AF-ME (0.36-0.45). The remaining 8 statistically significant estimates of non-fuel passenger costs are all below 0.20, with the lowest elasticity at 0.04-0.11 found in CA-NA. Thus, we can conclude that overall, increases in non-fuel per passenger costs have the smallest impact to airline pricing behavior.

There are two potential reasons to explain this result. Firstly, the weight of the non-fuel passenger costs is generally the smallest in airline's total operating costs. For instance, by our calculation, in year 2015 the weights of three costs types in total segmrnt costs for flight segment LHR-PEK are: fuel costs (41%), non-fuel flight costs (53.3%), and non-fuel passenger costs (5.7%). Therefore, increases in non-fuel passenger costs are less likely to have a huge impact on airlines' pricing. Secondly, literature has demonstrated that increases in the firm-level costs are much less passed onto passengers than the sector-wide cost changes *(2, 3)*. As a major part of the non-fuel passenger costs, the volume-related costs (in-flight services, meals, etc.) clearly belongs to the firm-level costs. Thus, our empirical results confirm that firm-level cost pass through is indeed less than sector-wide cost pass-through.

Overall, there is statistical evidence that airlines do pass through a significant proportion of operating costs onto passengers across different regional markets. However, the commonly assumed 100% cost pass-through is not supported by our empirical results. Rather, most of the estimated pass-through elasticities are below 0.5, after controlling for the key supply, demand, and competition effects on airfares in the model. Additionally, we found that increases in airline non-fuel flight costs will significantly impact airline pricing across all regional markets. In contrast, increases in airline fuel costs are unlikely to affect most of the ME-involved markets, as the fuel costs of many Gulf national flag airlines in these markets are significantly cheaper (*31*). Finally, changes in non-fuel passenger costs have the least impacts to airlines and the impacts are only significant to 14 markets out of 20.

To conclude this section, we compare the potential impacts of an emissions reduction policy that increases airline fuel costs on airfares, demand, and $CO_2$ emissions in two major regional markets. The fare model developed in this work is a core component of the updated aviation systems model AIM2015 *(21)*, which predicts the system-wide impacts of aviation technology-, operational-, and policy scenarios. Using the AIM2015, we simulate a carbon tax policy over three baseline scenarios. For sources of these baseline scenarios see Dray, *et al (21)*. Specifically, the three baseline scenarios are:

1. The worst-case scenario: low GDP growth to 2050, high oil prices, and pessimistic technology adoption (late availability date, high cost, low benefit).
2. The mid-case scenario: mid GDP growth to 2050, central oil prices, and mid-range technology adoption.
3. The best-case scenario: high GDP growth to 2050, low oil prices, and optimistic technology adoption (early availability date, low cost, high benefit).

Two regional markets with distinct cost pass-through elasticities are selected, i.e. AP-AP and EU-EU, where a carbon tax is introduced in 2015 at \$36/t$CO_2$ and linearly reaches to \$150/t$CO_2$ by 2050. Notably, this is a relatively high carbon tax scenario, compared to the highest carbon tax in the EU ETS to date at \$36 *(32)*. Figure 3 depicts first the key scenario inputs of GDP growth and oil prices, followed by the scenario projections for both regional markets.

According to Figure 3, demand in terms of RPK from 2015 to 2050 could increase the most under the best-case scenario in both markets (a.1 and a.2). In AP-AP, total RPK under the best case is projected to increase by 494%, 2 times the increase under the mid-case scenario, and 3.9 times the worst-case scenario. Demand in EU-EU follows the similar trend, with an increase under the best-case scenario by 353%, 1.9 times the mid-case scenario and 5.3 times the worst-case scenario. The strong demand growth of the best case is partially boosted by the projected low fares. According to b.1 and b.2, in both markets average fare per RPK turns out to be the lowest under the best-case scenario and the highest under the worst-case scenario. In addition, within each baseline scenario, fares fluctuate as fuel prices change (input.1) yet the fluctuation is more significant in AP-AP than in EU-EU. Finally, driven by the projected strong growth in demand, the total direct $CO_2$ emissions could increase the most under the best-case scenario (AP-AP 444% and EU-EU 294%), despite an optimistic assumption on low-carbon technological improvements.

Having compared how the baseline scenarios could change in future without any emissions reduction policy interventions, now we assess if a high carbon tax would make any differences on demand, fare, and $CO_2$ emissions in the two markets. Importantly, given that the fuel cost pass-through elasticity is higher in AP-AP (0.36-0.39) than in EU-EU (0.23-0.25) (TABLE 2), fares in AP-AP are expected to increase more compared to fares in EU-EU, after the introduction of the carbon tax. Consistent with our expectations, by 2050 fare per RPK in AP-AP (b.1) could be 12.5% (the best-case), 7.1% (the mid-case), and 3.4% (the worst-case) higher than those of the no-intervention projections, whereas fare per RPK in EU-EU is projected to increase only by 6.9% (the best-case), 3.8% (the mid-case), and 1.8% (the worst-case), respectively. Our results prove that airlines would adjust airfares based on their fuel cost elasticities in different regional markets.

As the results of the increased airfares, by 2050 demand in AP-AP (a.1) could reduce by 9.7% (the best-case), 5.7% (the mid-case), and 2.8% (the worst-case), respectively. Impacts on EU-EU demand are smaller due to the smaller increases in prices, with the post-policy RPK decrease by 6.2% (the best-case), 3.8% (the mid-case), and 2.0% (the worst-case), respectively, by 2050. The associated direct $CO_2$ emissions follow the similar trend. Compared with the no-intervention projections, emissions under the best-case scenario could drop by 9.6% in AP-AP and by 6.6% in EU-EU by 2050 if the carbon tax was introduced. Emissions reduction under the mid-base scenario is projected to be 5.4% in AP-AP and 3.7% in EU-EU. The worst-case scenario would be least affected with emissions only decreased by 2.5% in AP-AP and 1.8% in EU-EU.

## CONCLUSIONS

The research presented in this paper shows that airlines operating in different regional aviation markets may have distinct pricing responses to the market-based measures (MBMs), by explicitly modelling the cost pass-through of fuel costs per passenger, nonfuel costs per passenger, and nonfuel costs per flight. It contributes to the field by enabling future research to have more certainty on the potential cost pass-through of airlines when evaluating the economic impacts of MBMs to aviation. To our best knowledge, this is the first study that empirically estimates airline cost pass-through under competition at a global scale.

The coefficient estimates indicate that increases in airline fuel costs may have the greatest impacts to the intra-Asia Pacific regional market and the inter-market connecting Asia Pacific and Europe. In contrast, the Middle East-involved markets are unlikely to be affected by the fuel costs increases because fuel costs are considerably cheaper to the Gulf legacy carriers. Thus, in order to reduce emissions in the ME-involved markets, market-based policies need to increase not fuel costs but other airline operating costs in these markets. Changes in non-fuel flight costs are found to have significant impacts to all regional markets, although it would be more difficult to design MBMs that can affect the largely-fixed flight-based operating costs. Increases in non-fuel per passenger costs would have the lowest impact to airfares as it is largely influenced by increases in firm-level costs and also has the smallest share in airline's total operating costs.

Our results also provide some useful insights into the potential impacts of introducing a carbon tax on airline pricing in different regional markets. The application of the aviation systems model AIM2015 using the estimated cost pass-through elasticities suggests that such policy intervention may have important and different effects on airfares, demand, and $CO_2$ emissions. Without any policy interventions, the growth of aviation $CO_2$ emissions can only be drastically slowed down in a low GDP and high oil price future, as the result of a low growth in demand. In contrast, the introduction of a high carbon tax proves to increase airfares, leading to a nearly 10% reduction in $CO_2$ emissions in the most fuel costs-sensitive market AP-AP, even if GDP grows rapidly and oil prices are low. However, the carbon tax effects is likely to be smaller in markets with lower fuel costs elasticities. This finding also implies that air transport passengers in the fuel-costs elastic markets could pay higher airfares compared to passengers in the less elastic markets under a global carbon tax policy. Lastly, given that the ME-involved markets are not affected by carbon tax, airlines in these markets could obtain large windfall profits due to both the unaffected fuel costs and the increased airfares.

**ACKNOWLEDGMENTS**
This work is supported by EPSRC grant EP/M027031/1. We are grateful for their support. The first author also personally acknowledges the Chinese Scholarship Council (CSC) for the scholarship provided to his PhD.

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**TABLE 1 Definition of the fare model variables.**

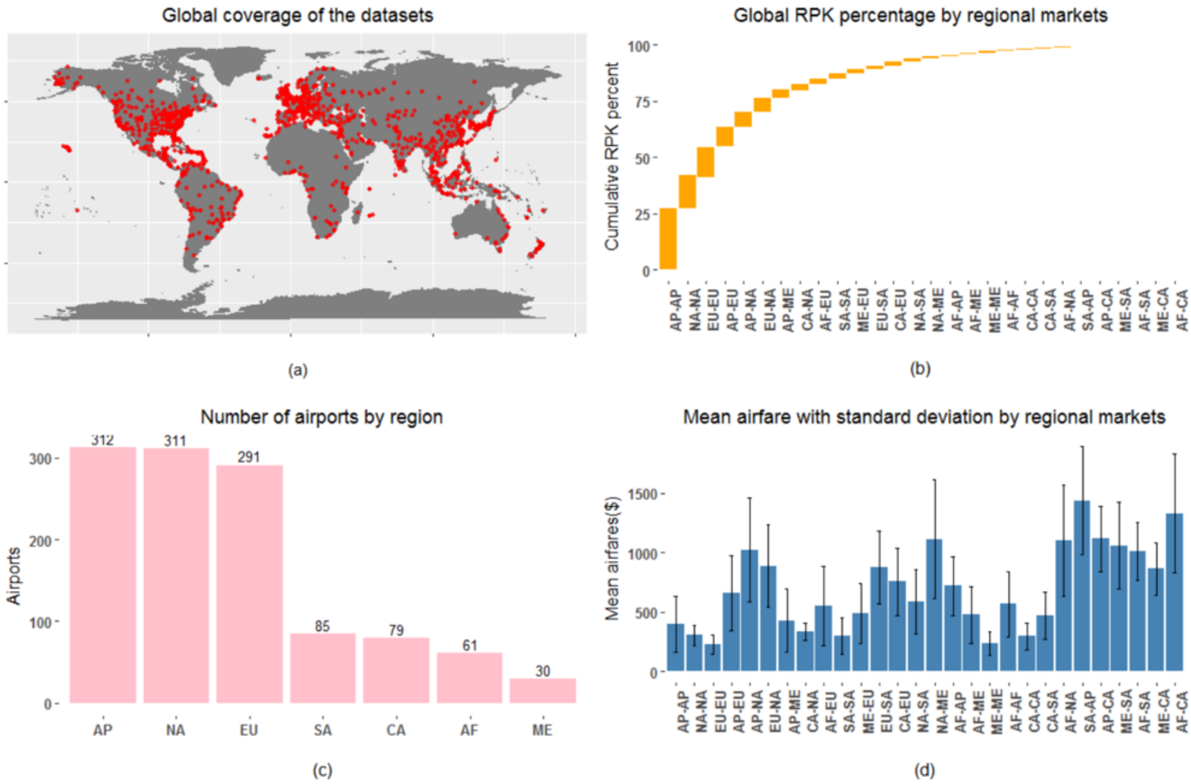
| Variable | Definition |
|---|---|
| Fare | The weighted average route fare (including taxes), calculated as the observed price weighted by the number of passengers paying this price by booking class. Fares are aggregated across all airlines on the same route. |
| FuelCostPerPax | The sum of average fuel costs per passenger of all flight segments used on the given itinerary. Flight segment total fuel costs are fuel costs of all aircraft operating on the given segment. |
| NonFuelCostPerFlt | The sum of average non-fuel per flight costs of all flight segments used on the given itinerary. |
| NonFuelCostPerPax | The sum of average non-fuel per passenger costs of all flight segments used on the given itinerary. |
| LegMeanHHI | O-D route-level Herfindahl-Hirschman Index (HHI). The HHI is calculated as the sum of squared market shares of all airlines in respective markets. Route HHI is measured by the geometric mean of segment HHIs covered by the route. A market contains all routes that connect the O-D metropolitan area, capturing competition at both local- and adjacent airport-pairs. |
| AirportMeanHHI | Endpoint airport-level market concentration measured by the average HHIs at origin and destination airport. A market here is defined to contain all airlines that depart from the origin airport, and all airlines that arrive at the destination airport. |
| CUIMean | Average airport Capacity Utilization Index (CUI) of the endpoint airports, calculated as the ratio of average aircraft movements during 16-hours daytime operating at a given airport over the airport's declared capacity. This variable is used to measure the effect of delays exogenously. |
| Freq | Annual total flight frequency on a given route. |
| Pax | Annual total number of passengers on a given route. |
| RouteShare | Ratio of O-D passengers on a given route over total O-D passengers between the O-D city pair. |
| Nlegs | The total number of flight segments used by a given route. Route characteristics that affect the demand. |
| HubsPass | The total number of hubs used by a given route. Route characteristics that affect the demand. |
| OriginCountry | Dummy variables of Origin Country. OriginCountry equals 1 if flying from country O (O = 2, 3, 4...). |
| DestCountry | Dummy variables of Destination Country. DestCountry equals 1 if flying to country D (D = 2, 3, 4...). |

**TABLE 2 Feasible Generalized Two-stage Least Squares (FG2SLS) estimation results[a].**

| Results for the 7 Intra-regional Markets | | | | | | |
|---|---|---|---|---|---|---|
| **Cost Variables** | **Market** | **Coef.** | **Std. Error** | **Pass-through** | **Obs.** | **Adj.$R^2$** |
| ln(FuelCostPerPax) | AP-AP | 0.375*** | 0.008 | 0.36-0.39 | 29,880 | 0.854 |
| | SA-SA | 0.238*** | 0.018 | 0.20-0.28 | 3,519 | 0.859 |
| | EU-EU | 0.237*** | 0.006 | 0.23-0.25 | 43,263 | 0.532 |
| | AF-AF | 0.233*** | 0.021 | 0.20-0.27 | 2,802 | 0.838 |
| | NA-NA | 0.200*** | 0.004 | 0.19-0.21 | 70,429 | 0.574 |
| | CA-CA | 0.168*** | 0.015 | 0.14-0.20 | 2,190 | 0.838 |
| | ME-ME | 0.007 | 0.053 | Not Significant | 626 | 0.864 |
| ln(NonFuelCostPerFlt) | ME-ME | 0.662*** | 0.063 | 0.55-0.77 | 626 | 0.864 |
| | SA-SA | 0.361*** | 0.019 | 0.32-0.40 | 3,519 | 0.859 |
| | AF-AF | 0.270*** | 0.021 | 0.24-0.30 | 2,802 | 0.838 |
| | AP-AP | 0.214*** | 0.008 | 0.20-0.23 | 29,880 | 0.854 |
| | CA-CA | 0.163*** | 0.014 | 0.14-0.19 | 2,190 | 0.838 |
| | NA-NA | 0.154*** | 0.003 | 0.15-0.16 | 70,429 | 0.574 |
| | EU-EU | 0.154*** | 0.005 | 0.15-0.16 | 43,263 | 0.532 |
| ln(NonFuelCostPerPax) | SA-SA | 0.584*** | 0.051 | 0.48-0.68 | 3,519 | 0.859 |
| | AF-AF | 0.276*** | 0.046 | 0.20-0.36 | 2,802 | 0.838 |
| | AP-AP | 0.156*** | 0.013 | 0.13-0.18 | 29,880 | 0.854 |
| | NA-NA | 0.152*** | 0.009 | 0.14-0.17 | 70,429 | 0.574 |
| | EU-EU | 0.069*** | 0.007 | 0.06-0.08 | 43,263 | 0.532 |
| | ME-ME | 0.146 | 0.255 | Not Significant | 626 | 0.864 |
| | CA-CA | -0.046 | 0.031 | Not Significant | 2,190 | 0.838 |
| **Results for the 13 Inter-regional Markets** | | | | | | |
| **Cost Variables** | **Market** | **Coef.** | **Std. Error** | **Pass-through** | **Obs.** | **Adj.$R^2$** |
| ln(FuelCostPerPax) | AP-EU | 0.339*** | 0.017 | 0.31-0.37 | 12,313 | 0.798 |
| | EU-SA | 0.321*** | 0.038 | 0.25-0.39 | 2,623 | 0.662 |
| | CA-NA | 0.232*** | 0.010 | 0.21-0.25 | 8,487 | 0.534 |
| | EU-NA | 0.217*** | 0.018 | 0.18-0.25 | 11,193 | 0.520 |
| | NA-SA | 0.181*** | 0.041 | 0.12-0.24 | 2,366 | 0.700 |
| | AP-NA | 0.162*** | 0.025 | 0.11-0.21 | 6,302 | 0.567 |
| | AF-EU | 0.151*** | 0.023 | 0.11-0.19 | 4,496 | 0.877 |
| | CA-EU | 0.141*** | 0.033 | 0.08-0.20 | 1,754 | 0.654 |
| | EU-ME | 0.118*** | 0.035 | 0.07-0.17 | 3,286 | 0.775 |
| | AF-AP | 0.056** | 0.022 | 0.01-0.10 | 1,910 | 0.866 |
| | AP-ME | 0.004 | 0.018 | Not Significant | 3,579 | 0.865 |
| | NA-ME | 0.011 | 0.053 | Not Significant | 1,399 | 0.651 |
| | AF-ME | -0.009 | 0.022 | Not Significant | 1,093 | 0.938 |
| ln(NonFuelCostPerFlt) | AF-ME | 0.406*** | 0.025 | 0.36-0.45 | 1,093 | 0.938 |
| | AF-AP | 0.367*** | 0.023 | 0.33-0.41 | 1,910 | 0.866 |
| | EU-ME | 0.335*** | 0.033 | 0.29-0.38 | 3,286 | 0.775 |
| | NA-ME | 0.325*** | 0.069 | 0.20-0.45 | 1,399 | 0.651 |
| | CA-EU | 0.278*** | 0.041 | 0.20-0.35 | 1,754 | 0.654 |
| | NA-SA | 0.278*** | 0.038 | 0.22-0.34 | 2,366 | 0.700 |
| | AP-NA | 0.274*** | 0.028 | 0.22-0.33 | 6,302 | 0.567 |
| | AP-ME | 0.266*** | 0.016 | 0.24-0.30 | 3,579 | 0.865 |
| | AF-EU | 0.259*** | 0.020 | 0.22-0.29 | 4,496 | 0.877 |
| | EU-SA | 0.222*** | 0.044 | 0.15-0.30 | 2,623 | 0.662 |
| | EU-NA | 0.172*** | 0.021 | 0.13-0.21 | 11,193 | 0.520 |
| | AP-EU | 0.110*** | 0.015 | 0.08-0.14 | 12,313 | 0.798 |
| | CA-NA | 0.075*** | 0.011 | 0.06-0.09 | 8,487 | 0.534 |
| ln(NonFuelCostPerPax) | AP-NA | 0.253*** | 0.014 | 0.23-0.28 | 6,302 | 0.567 |
| | AP-EU | 0.183*** | 0.016 | 0.16-0.21 | 12,313 | 0.798 |
| | AF-EU | 0.168*** | 0.024 | 0.12-0.21 | 4,496 | 0.877 |
| | EU-SA | 0.149*** | 0.026 | 0.10-0.20 | 2,623 | 0.662 |
| | EU-ME | 0.124*** | 0.032 | 0.07-0.18 | 3,286 | 0.775 |

| | | | | | |
|---|---|---|---|---|---|
| NA-ME | 0.114** | 0.038 | 0.04-0.19 | 1,399 | 0.651 |
| AF-AP | 0.111** | 0.044 | 0.03-0.19 | 1,910 | 0.866 |
| EU-NA | 0.080*** | 0.016 | 0.05-0.11 | 11,193 | 0.520 |
| CA-NA | 0.072*** | 0.018 | 0.04-0.11 | 8,487 | 0.534 |
| AP-ME | -0.038 | 0.032 | Not Significant | 3,579 | 0.865 |
| CA-EU | -0.039 | 0.034 | Not Significant | 1,754 | 0.654 |
| NA-SA | -0.072 | 0.038 | Not Significant | 2,366 | 0.700 |
| AF-ME | -0.056 | 0.061 | Not Significant | 1,093 | 0.938 |

*** Significant at the 0.1% level.
** Significant at the 1% level.
* Significant at the 5% level.
[a] Markets ranked descendingly by the pass-through elasticity within each cost variable.




NOTE: NA=North America, CA=Central America, SA=South America, EU=Europe, ME=Middle East, AF=Africa, AP=Asia and Pacific

**FIGURE 1 Descriptive summary of datasets.**

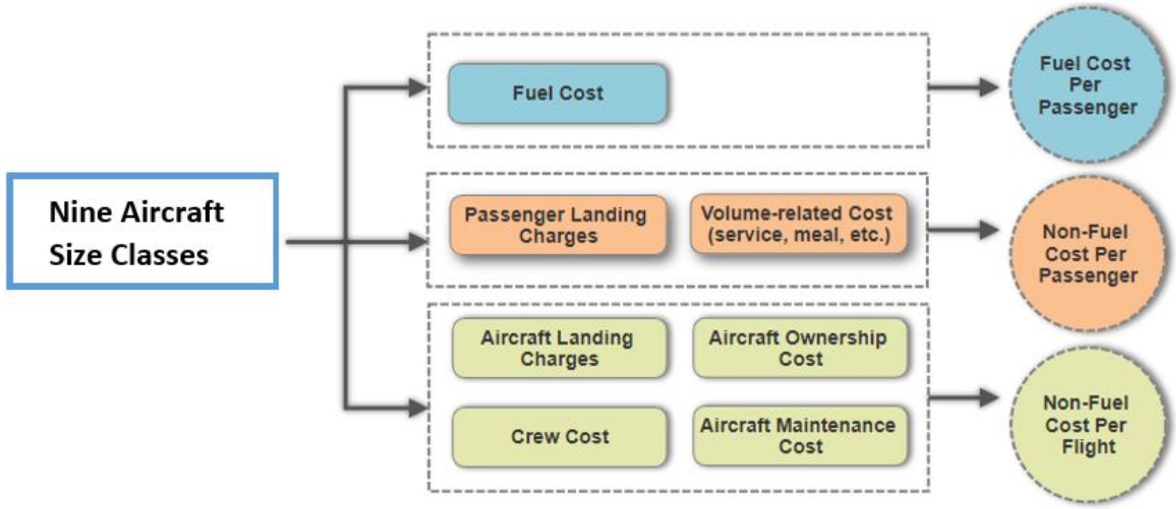



**FIGURE 2 Procedure for constructing airline operating costs variables.**

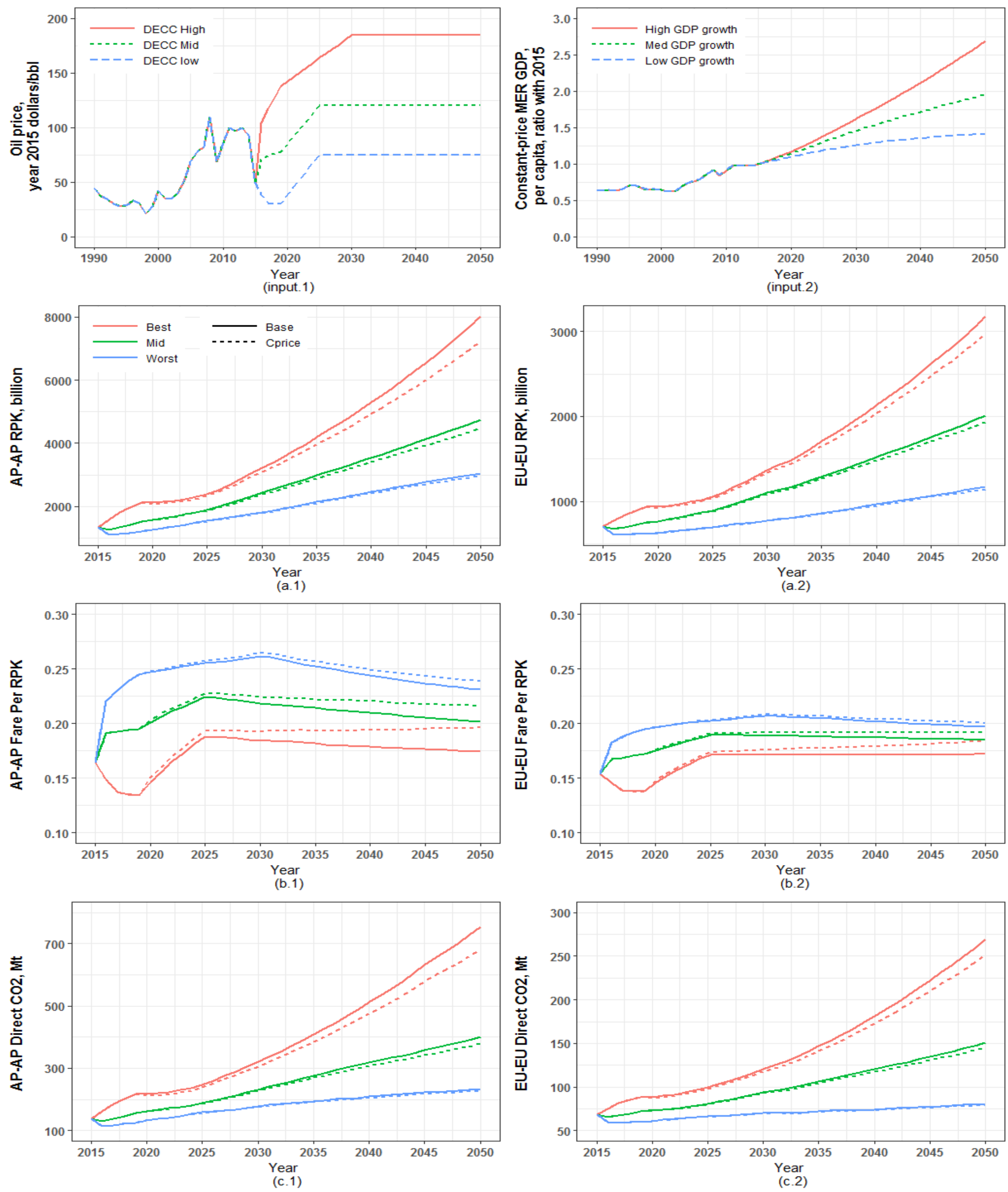



**FIGURE 3 AIM2015 projections on demand, average fare, and direct $CO_2$ emissions in AP-AP and EU-EU regional airline markets.**