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Imperfect reversibility of air transport demand: Effects of air fare, fuel prices and price transmission

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Abstract

There are recent evidence that air transport demand may not have a perfectly reversible relationship with income and jet fuel prices, as is assumed in most demand models. However, it is not known if the imperfectly reversible effects of jet fuel price are a result of asymmetries in the supply side, i.e. asymmetries in cost pass through from fuel prices to air fare, or of demand side behavioural asymmetries whereby people value gains and losses differently. This paper uses US time series data and decomposes air fare and fuel price into three component series to develop an econometric model of air transport demand that is capable of capturing the potential imperfectly reversible relationships and test for the presence or absence of reversibility. We find that air transport demand shows asymmetry with respect to air fare, indicating potential imperfect reversibility in consumer behaviour. We also find evidence of asymmetry and hysteresis in cost pass-through from jet fuel prices to air fare, showing rapid increases in airfare when fuel prices increases but a slower response in the opposite direction.

Keywords

Air transport demand, price transmission, cost pass-through, reversibility, asymmetric response, hysteresis

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1. Introduction

Air transport demand is an important parameter for transport planners, airlines, airports, aircraft manufacturers and other related stakeholders. As such, there is a substantial literature on modelling and forecasting demand for passenger air transport (e.g. Profillidis 2000, Lim et al. 2008, Tsekeris 2009, Department for Transport 2013, Wadud 2011 and 2013), all of which *assume* that demand is perfectly reversible with respect to its drivers. Perfect reversibility of demand implies that the demand response to an increase in one of the driving factors (e.g. price or income) is exactly of the same magnitude and of opposite direction as the response to an equal reduction in the same factor, irrespective of previous history of that driving factor. Therefore, for a perfectly reversible price effect, demand reductions during a rise in price will be fully compensated by demand increases during similar price falls (or vice versa). Such assumption has been challenged in other economic relationships in the area of transport and energy, such as those between oil price and energy demand (e.g. Dargay 1992, Gately 1992) or between income and car ownership (e.g. Pendyala et al. 1995, Dargay 2001). Along the same vein, Wadud (2014) was first to argue that air transport demand could also show an imperfectly reversible relationship with its demand drivers due to various reasons.

Wadud (2014) successfully found evidence that air transport demand shows an imperfectly reversible relationship with respect to *jet fuel prices*, but did not investigate further the potential reasons or mechanisms behind this. Air travel demand could show imperfectly reversible relationship with respect to fuel prices due to behavioural, demand side reasons (whereby people naturally react differently to price increases and decreases) or to other supply side asymmetric responses to changes in jet fuel prices (whereby rises and falls in input prices affect air fare differently). For example, it is possible that the air travel demand is a perfectly reversible function of air fare, yet air fare is imperfectly reversible with respect to fuel prices, the combination of which would result in the imperfect reversibility of air travel demand with respect to jet fuel prices, as found by Wadud (2014). Given air fare itself is an important planning variable it is therefore important to understand whether the imperfect reversibility of air transport demand holds for air fare too, or whether it is indeed perfectly reversible as in the hypothetical example above. This paper addresses this important gap. The primary focus is to understand and compare the effects of jet fuel prices and air fare and, specifically, the role of supply side cost pass-through (from input costs to air fare) in the asymmetric demand responses.

The paper is organized as follows. Section 2 reviews the literature on reversible and asymmetric responses while section 3 discusses imperfect reversibility in the context for air travel. Section 4 describes the data and section 5 explains the econometric modelling methods used in the study. Section 6 presents the findings while section 7 draws conclusions.

2. Literature on imperfect reversibility

Imperfect reversibility in economic functions was first studied in agricultural economics by Wolffram (1971) in the context of supply functions and then gained prominence in the area of transportation and energy through the works by Gately (1992) and Dargay (1992) in the context of demand for petrol, oil or transport services (vehicle miles travelled). Although the classical demand theory does not differentiate between the impacts of similar increases and decreases of the demand drivers and assumes that they are equal but opposite, applied researchers have long speculated that consumers react more to price increases than to reductions. This has been demonstrated by Dargay (1992) and Gately (1992) in a series of studies on oil demand and prices in different geographical regions in the world and the asymmetric response was attributed primarily to irreversible technology fixation: a rise in price encourages the installation of fuel efficient technologies, which results in lower consumption even when the prices go down afterwards. On the other hand, Kahneman and Tvesrky's (1979) seminal work on prospect theory shows that consumers value losses and gains differently and may not seek to maximize their utility rationally (which is the basis of classical demand theory). Therefore there could be behavioural factors that could also result in an imperfectly reversible demand response. For example, Young's (1983) work on asymmetric price responses of cigarette demand hinges on behavioural factors, rather than on technology fixation.

Imperfectly reversible effects can be classified into two types: asymmetry and hysteresis, although often no explicit distinction is made. Strictly speaking, asymmetry is the divergence of demand responses during price (or other demand driver) increases and decreases, without any reference to the price (or other demand driver) history. Asymmetry is important to understand if demand reductions during a fall in income can be compensated during similar rise in income, or similar questions involving other demand drivers. On the other hand, hysteresis is the difference in responses to a demand driver depending on the history of the demand driver. It is more suited to answer longer run questions such as to compare price or income elasticities of two different time periods. Both of the effects result in a 'kinked' demand curve with respect to the driving factor instead of a continuous one (see Wadud 2014 for an illustration of a kinked demand curve). It is possible for demand to show asymmetry, but not hysteresis or vice versa (e.g. see Dargay and Gately 1997), but generally both effects tend to be closely related and are present together. While earlier studies prior to Gately (1992) focussed solely on asymmetric effects, both asymmetry and hysteresis are now jointly modelled and tested when studying imperfect reversibility.

There is substantial evidence on imperfectly reversible functions in economics - both for demand as well as supply functions. The early evidence was on supply functions where asymmetry in price transmission or cost pass-through was the major focus. Wolffram (1971) and Traill et al. (1978) are the major early contributions in this area. Bacon (1991) termed the asymmetry in supply functions as the 'rocket and feather' response, whereby the price of a product shoots up quickly when the input prices increase while it falls slowly when input costs decrease. Such asymmetry in cost pass-through has been studied in detail for crude oil and retail petrol prices - and most studies find evidence in favour of an asymmetric response (Bacon 1991, Borenstein et al. 1997). On the demand side, Dargay (1992), Gately (1992), Dargay and Gately (1995, 1997), Gately and Huntington (2002) or Adeyemi et al. (2010) worked on transport, petrol or oil demand, while there are earlier works by Young (1983) on cigarette demand or by Bidwell et al. (1995) on telephone calls.

3. Imperfect reversibility in air transport demand

In the aviation sector, Wadud (2014) was the first to propose the possibility of imperfectly reversible effects of income and jet fuel prices on air transport demand in the USA. The study explained how imperfect reversibility can occur in air transport demand and provided econometric evidence of such occurrence for revenue passenger miles (RPM) as a demand metric. The study decomposed income and fuel prices each into three distinct series to model imperfect reversibility of demand and find that both income and jet fuel price impacts indeed show asymmetry and hysteresis. While the asymmetric effects on income can result from behavioural factors such as habits and practices, Wadud (2014) could not “detect if the asymmetry in the fuel price response is due to behavioural reasons, or because of asymmetric fuel cost pass-through by the airlines, or both”. Unlike in the studies of petrol demand or VMT demand by Dargay (1992) and Gately (1992), where petrol or diesel prices were a direct factor to the costs of driving, jet fuel prices do not enter the utility function of the air transport passengers directly. Instead, fuel prices affect the airlines' cost function and thus air fare, which in turn determines demand from a passenger's perspective. In between, there is a scope for adjustments (reversible or imperfectly reversible) during the transmission of fuel price to air fare as well. Especially, following earlier evidence on asymmetric 'rocket and feather' cost pass-through in various businesses, and recent such evidence specific to airlines (Escobari 2013), it is quite possible that jet fuel prices have an imperfectly reversible effect on air fare. In such a case, the imperfectly reversible demand response to jet fuel prices in Wadud (2014) could be a direct result of asymmetric cost pass-through, and no inference can be made if air transport passengers show imperfectly reversible responses to changes in the air fare/ticket prices.

Elaborating further, air transport demand (D) can be expressed as a function of jet fuel prices (P), income (Y) and a vector of other explanatory factors ($\boldsymbol{X}$ or $\boldsymbol{X'}$) as follows (assuming a constant elasticity logarithmic demand function):

$$lnD = \alpha' lnY + \gamma lnP + \boldsymbol{\theta}'\boldsymbol{X}' \tag{1}$$

Expressed in terms of air fare ($FARE$), the demand function becomes:

$$lnD = \alpha lnY + \beta lnFARE + \boldsymbol{\theta X} \tag{2}$$

where, air fare is a function of jet fuel prices (P) and other explanatory factors ($\boldsymbol{Z}$):

$$lnFARE = \delta lnP + \boldsymbol{\theta}''\boldsymbol{Z} \tag{3}$$

On the other hand, successive differentiation of lnD with respect to lnP yields the following:

$$\frac{\partial lnD}{\partial lnP} = \frac{\partial lnD}{\partial lnFARE} \times \frac{\partial lnFARE}{\partial lnP}$$

or, $\gamma = \beta \times \delta$ (4)

i.e. elasticity of air transport demand with respect to jet fuel prices (γ) is equal to the elasticity of air transport demand with respect to air fare (β), multiplied by the elasticity of air fare with respect to fuel prices (δ). It follows from Eq. (4) that there can be three distinct possibilities consistent with an imperfectly reversible demand with respect to fuel price (i.e. γ = imperfectly reversible):

1. air fare is an imperfectly reversible function of fuel price, demand is an imperfectly reversible function of air fare, i.e. β and δ are both imperfectly reversible;
2. air fare is a perfectly reversible function of fuel price but demand is an imperfectly reversible function of air fare, i.e. β is reversible, but δ is imperfectly reversible; and
3. demand is a perfectly reversible function of air fare, but airfare is an imperfectly reversible function of jet fuel prices, i.e. δ is reversible, but β is imperfectly reversible.

The primary focus of this research is to investigate, understand and compare the imperfectly reversible effects of fuel prices and air fare, and the role of reversibility in the transmission of fuel prices to air fare. The comprehensive model specification, however, allows for imperfect reversibility of the income effects as well.

4. Data

The most widely used metric to measure passenger transport demand is passenger miles, while for air transport this is revenue passenger miles (RPM). Accordingly, Wadud (2014) had earlier used monthly observations on RPM in his study of imperfect reversibility in air transport demand with respect to income and jet fuel price. RPM can be decomposed into revenue passenger enplanement (RPEN) and average miles per passenger (MPP) and generally RPM follows the seasonal cycles and trend of RPEN as the changes in MPP are much slower than the changes in RPEN. Since one of the demand drivers of our interest is air fare, which directly depends on the distances travelled (Rama-Murthy 2006), endogeneity can be an important consideration in estimating an econometric model with RPM as the demand metric. The predominant method to control for endogeneity of the explanatory factors in econometric models is the instrumental variable technique. However, finding an appropriate instrument that is correlated with the endogenous variable, but not with the error term, can be fraught with difficulties.[1] We therefore choose RPEN as the metric to represent air transport demand in the USA.[2] In our econometric model, the dependent variable is RPEN per capita per day ($RPEN^{cd}$) in order to control for population and different number of days in the months.[3]

Monthly RPEN data for the US carriers is collected from the Bureau of Transport Statistics (BTS, 2014), with temporal coverage from 1979 to 2012. This time period includes not only the large fuel price increases of the second oil shock, but also the recent fuel price rises since 2005 and the sustained recessions around 2008-2009. Monthly jet fuel (kerosene type) prices were collected from Energy Information Administration (2013) and converted to real prices using Bureau of Labor Statistics' (BLS, 2014a) consumer price indices (CPI). Income is represented by monthly real disposable income from National Income and Product Account (NIPA) of the Bureau of Economic Analysis (2013). Population data used to normalize RPEN in per capita terms is from the same source as well. Note that, unlike Wadud (2014), the entire time period falls after the airline-deregulation in the USA. Fig. 1 presents the monthly evolution of RPM, RPEN and RPEN per capita per day. As expected, the growth effect is tempered for the per capita normalized series.

[Fig. 1]

Monthly domestic air fare information is available from BLS (2014b) as air travel price index (ATPI-BLS) for our entire time period, which can be converted to real terms using the CPI. Annual domestic

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[1] As Maddala (1977) puts it: 'where do you get such a variable?'
[2] RPEN and air fare can still be endogenous. For example, airlines could opt to lower fares in low load-factor flights to keep hold of the slot. This is expected to be a short-run and local-scale phenomenon, since in the long run airlines have to be profitable and they cannot carry loss-bearing markets for long. Given our long, aggregate time series when entry/exit is not prevented, we do not consider it explicitly further.
[3] This avoids the inclusion of population as a dependent variable, which can be problematic because of its high correlation with income.

air fare is also available from Airlines for America (A4A 2014), which is an aggregation of BTS' airline origin destination survey (DB1B data series). BTS (2014) also develops a quarterly air travel price index (ATPI-BTS) for a shorter time series, from 1995. While the ATPI-BTS and annual domestic air fare from A4A matches closely, there is a substantial discrepancy between real ATPI-BLS and real air fare from A4A. Specifically, A4A shows a consistent trend of reduction in domestic air fares (despite some increase in MPP) apart from the early years of our time series (possibly due to the second oil shock), while the annualized series from ATPI-BLS does not show such a clear reduction trajectory. The major reason is possibly the sampling of primarily SABRE reservation data by the BLS, while A4A data is from 10% sample of tickets, which include substantially discounted internet purchases as well.[4] We therefore take the A4A annual air fare series as the correct data, but use the monthly variations from ATPI-BLS to construct a monthly time series of domestic fare ($FARE$).[5]

5. Methods

In an econometric demand model, income, fuel prices or air fare generally enter the model specification directly, often in a logarithmic form. In such a specification, positive and negative changes in the explanatory factors have the same effect on demand, whereas our objective is to differentiate between the demand responses to a positive and a negative change, or between a sub-maximum air fare, fuel price or income recovery and an above maximum increase in air fare, fuel price or income. Following Wolffram (1971), Gately (1992), Dargay (1992) and Dargay and Gately (1997), Wadud (2014) decomposed the fuel price and income series each into three components: a monotonically increasing series of the historical maximum value of the variable, a monotonically increasing series of cumulative rises, as long as the rise does not increase the value of the variable above previous maximum, and a monotonically decreasing series of cumulative falls. We follow a similar decomposition technique in this work, too, and mathematically the decomposition is expressed as follows:

$$V_t^{max} = max(V_0, \dots., V_t) \tag{5}$$

$$V_t^{rec} = \sum_{i=0}^{t} max\{0, (V_{i-1}^{max} - V_{i-1}) - (V_i^{max} - V_i)\} \tag{6}$$

$$V_t^{fall} = \sum_{i=0}^{t} min\{0, (V_{i-1}^{max} - V_{i-1}) - (V_i^{max} - V_i)\} \tag{7}$$

V_t^{max} refers to the maximum value of the variable of interest (fuel price, P, air fare $FARE$, or income, Y, in logarithms) up to the time t. This is monotonically increasing and changes only if the variable in

[4] The discrepancy has been reducing in recent years as BLS starts sampling internet ticket prices too.
[5] Specifically, constructed air fare price series=monthly ATPI-BLS*annual A4A air fare/annual ATPI-BLS, all real.

time t is larger than the maximum value at time t-1. V_t^{fall} refers to the cumulative series of the falls in the value of the variable, this is monotonically decreasing, and is always negative. V_t^{rec} refers to the cumulative rise or recovery of the value of the variable, when it is below V_t^{max}. Therefore it represents the sub-maximum cumulative rises in the variable, and is again monotonically increasing only. In order for the first type of imperfect reversibility, or asymmetry, to hold with respect to the variable, the parameter estimates for V_t^{fall} and V_t^{rec} should be different. On the other hand, for the second type of imperfect reversibility to hold, parameters related to V_t^{max} and V_t^{rec} should be different.

The primary explanatory variables in our reduced form econometric demand model are air fare ($FARE$) and kerosene type jet fuel prices (P), in addition to income per capita (Y). We run two separate models with P and Y, and Y and $FARE$ as explanatory factors to independently compare the effects of fuel price and air fare, our primary objective. All of these variables enter the specification in their decomposed forms, as described above and plotted in Figs. 2, 3 and 4. Following Ito and Lee (2005) and Wadud (2014), we also include monthly unemployment rate (U) as an explanatory factor in both the models. We include several dummy variables in order to control for external events that could have significantly affected air transport demand during the sample time period. These include the air controllers strike in 1981 which resulted in the mass discharge of US air controllers during the Reagan administration (D_1) and the 9-11 terrorist attack in 2001. Following Wadud's (2014) earlier finding that the first and second gulf war and the SARS scare of 2003 did not have a statistically significant effect on RPM, we do not include these in the final model.[6] The 9-11 terrorist attack in the USA had a profound effect on the aviation industry and air transport demand in the USA. One dummy variable for September 2001 (D_2) is used to represent the sudden dip in passenger patronage in that specific month, which is primarily a result of supply side disruption (flights banned in US airspace for a few days). In addition, the event led to various other security measures, which made air travel unpleasant, and may have led to a sustained demand impact, at least for a few years (Ito and Lee 2005). Therefore, a second dummy variable which attains a value of 1 for three years after September 2001 (D_3), is added to the specification.[7] Also, we add a dummy variable (D_4) for the December months for those years when the thanksgiving weekend falls in that month, so that the additional December air travel can be explained.

[Fig. 2]

[Fig. 3]

[6] When tested, these were statistically insignificant in the current models, too.
[7] We have also used alternate time periods of 2 and 4 years. 3 years produced best regression results.

[Fig. 4]

The decomposed variables in income, air fare and fuel price are all non-stationary by construction, as they are either monotonically increasing or decreasing. Regressions with non-stationary variables can often be spurious, although Engle and Granger (1987) show in their seminal work that there could be a specific combination of the non-stationary variables that is stationary. In such cases, there exists a valid long run 'cointegrating' relationship between the variables, which can be estimated via the Ordinary Least Squares (OLS). The OLS residuals for the regression need to be stationary for the relationship to be 'cointegrating' and stationarity tests (e.g. unit root tests) on these residuals act as a test for cointegration as well. The use of monthly data in this study raises the possibility of seasonal unit roots, however, following Osborn's (1993) justifications on using seasonal dummies, we do not consider seasonal unit roots and control for the seasonal differences in air transport demand through monthly dummy variables (MD) in the model.

Although the use of OLS in a static equation framework as per Engle and Granger (1987) is widespread to determine the long-run cointegrating relationships, Hendry (1986) and Phillips and Loretan (1991) argued that the inference on the cointegrating parameter estimates from static OLS estimation can be misleading because of the presence of residual autocorrelation among the errors. Accordingly, Banerjee et al. (1986) suggest that the long run parameters should be determined from a dynamic model. As long as the dynamics are specified such that the residuals are not autocorrelated, then the inference on the parameter estimates are valid, provided a long-run cointegrating relationship exists (Patterson 2000). We therefore follow a dynamic stock adjustment modelling approach in this study, whereby the lags of the dependent variable are added as an explanatory factor. We then test if the 'implied' long-run relationship from the dynamic model is spurious or not.

The final specifications of passenger air travel demand for the two models are as follows:

$$\text{Model 1: } RPEN_t^{cd} = \mu + \alpha_{max} Y_t^{max} + \alpha_{rec} Y_t^{rec} + \alpha_{fall} Y_t^{fall} + \beta_{max} FARE_t^{max} + \beta_{rec} FARE_t^{rec} + \beta_{fall} FARE_t^{fall} + \kappa U_t + \sum_{j=1}^{4} \lambda_j D_{jt} + \sum_{k=2}^{12} \varphi_k MD_{kt} + \sum_{i=1}^{l} \omega_i RPEN_{t-i}^{cd} + \varepsilon_t \quad (8)$$

$$\text{Model 2: } RPEN_t^{cd} = \mu' + \alpha'_{max} Y_t^{max} + \alpha'_{rec} Y_t^{rec} + \alpha'_{fall} Y_t^{fall} + \gamma_{max} P_t^{max} + \gamma_{rec} P_t^{rec} + \gamma_{fall} P_t^{fall} + \kappa' U_t + \sum_{j=1}^{4} \lambda'_j D_{jt} + \sum_{k=2}^{12} \varphi'_k MD_{kt} + \sum_{i=1}^{l} \omega'_i RPEN_{t-i}^{cd} + \varepsilon'_t \quad (9)$$

Given that aviation RPEN does not have a direct causal effect on income, price of oil, ticket prices/fare or unemployment, we infer that the right side variables are all exogenous and thus modelling for a single cointegration vector suffices. Since the continuous variables (RPEN, fuel price, air fare, income and unemployment series) are all expressed in logarithms, the parameter estimates directly provide the elasticities of RPEN with respect to the corresponding variables. Note that the perfectly reversible models are special cases of the imperfectly reversible models in Eqs. (8) and (9). For a perfectly reversible response to income, $\alpha_{max}=\alpha_{rec}=\alpha_{fall}$ or $\alpha'_{max}=\alpha'_{rec}=\alpha'_{fall}$, while for perfectly reversible effects of air fare or fuel price, $\beta_{max}=\beta_{rec}=\beta_{fall}$ or $\gamma_{max}=\gamma_{rec}=\gamma_{fall}$. Therefore these tests for equality of the parameters also act as a test for the choice between the perfectly and imperfectly reversible models. Note that Eq. (4) can also be used to indirectly infer the changes in air fare with respect to the changes in jet fuel prices. Therefore, the relationship in Eq. (4) can be used to statistically test the presence of imperfect reversibility or asymmetry in cost pass-through.

6. Results and discussions

Monthly time series data generally show a strong correlation at annual interval. Therefore we add a 12th lag of the dependent variable in both the models. We then test for the addition of lags 1, 2 and so forth, and find that the first lag (and the 12th lag as mentioned above) can provide a parsimonious model with no autocorrelation in the residuals for both models. We employed AIC and BIC for model fit, Breusch-Godfrey LM test (Breusch 1978, Godfrey 1978), Durbin (1970) alternate h-test for residual autocorrelation, Shapiro and Wilk (1965) test for residual normality and Bartlett (1955) test for white-noise of the residuals. Both of the models presented in Table 1 pass all of these specification tests. We also calculate the 'implied' long-run parameters of all the explanatory factors, which give us an 'implied' cointegration vector as per Patterson (2000), and then test if the residuals of the cointegrating vector are stationary through Dicky-Fuller (1979) GLS test for a unit root. The residuals were stationary for both the models, ensuring that the long run relationships between the variables as implied by the respective dynamic models are not spurious. As per our earlier discussion, inference is based on the dynamic models, though. Table 1 presents the estimation results for the two models for air travel demand in the USA.

[Table 1]

For both models, monthly dummies are significant for all of the months, indicating the seasonality in air travel demand. There was a statistically significant reduction in passenger enplanement due to air traffic controllers' strike and subsequent mass-firing (D_1). During the years when thanksgiving weekend falls in December (D_4), demand is larger than when they are contained entirely in November. A large and statically significant negative parameter estimate for D_2 indicates a large reduction in passenger enplanement in September 2001 as a result of 9-11. Negative and statistically significant estimate for D_3 indicates the sustained reduction in passenger patronage post 9-11 years.

All of these results follow a priori expectations. A rise in unemployment reduces air travel demand, as evident from Model 1, but the evidence was less strong for Model 2.

The parameter estimates in Table 1 refer to the short run demand elasticities with respect to corresponding continuous explanatory factors. Table 2 presents the calculated longer run elasticities with respect to the three decompositions of income, air fare and fuel price. There are marginal differences between the two models in the estimates for three income elasticities, but the elasticities follow the same pattern in both models: income elasticities for a post-recession income recovery phase is larger than the income elasticities during a recession, or the income elasticities for income above a previous maximum. Wald test for the equality of the parameters α_{max}=α_{rec}=α_{fall} and α'_{max}=α'_{rec}=α'_{fall} for the two models reject the null of equality (F=18.63 and 9.78 respectively), suggesting air transport demand is not reversible with respect to income (Table 3). Tests for symmetric effects of income rises and falls, i.e. for α_{rec}=α_{fall} and α'_{rec}=α'_{fall}, are also rejected (F=8.03 and 11.67 respectively), indicating statistically significant asymmetry in the effects of income on air transport demand. Equality tests for α_{max}=α_{rec} and α'_{max}=α'_{rec} (F=33.17 and 7.20 respectively) confirms that income elasticities during a post-recession recovery of income and during the increases of income above previous maximum values are different, providing evidence of the presence of hysteresis effects. Specifically, the effect of rising income on air transport demand is larger during the income recovery phases. Outside aviation, asymmetric effects on income was also found for car ownership and car travel (Dargay 2001).

[Table 2]

Table 3 also presents the tests for equality of the elasticities with respect to the three fuel decompositions of fuel price and air fare. Our primary interest is the model with air fare as the explanatory factor (Model 1), where the null hypothesis of $\beta_{max} = \beta_{rec} = \beta_{fall}$ is rejected by the Wald test (F=5.37), suggesting that air transport demand shows imperfect reversibility with respect to air fare. There is also a strong statistical evidence of asymmetric responses during air fare rises and falls (Wald F statistics for $\beta_{rec} = \beta_{fall}$ is 7.54). Since the elasticities with respect to air fare is independent of any cost pass-through effects of the supply side, the asymmetric response to air fare is possibly a result of behavioural factors. Our results thus tend to agree with the prospect theory of Kahneman and Tversky (1979) that suggest that people tend to value losses more than gains. It is also important to note that, although air transport demand shows a 'statistically' significant asymmetry with respect to air fare, the magnitude of the asymmetry is fairly small for practical purposes: the short run elasticity of demand during an air fare rise is 0.143, while that during a fall in air fare is 0.113. In the long run, however, the differences are magnified: the long run elasticities of air transport demand with respect to air fare during rising and falling air fares are 0.526 and 0.417 respectively.

[Table 3]

The Wald test for $\beta_{max} = \beta_{rec}$ cannot be rejected (F=2.17) for Model 1, which suggests the possibility of no hysteresis effects in air transport demand with respect to air fare. This could indeed be a genuine finding, yet we also note that the air fare was at its maximum during early 1980's following the second oil shock and when the effects of deregulation were still coming into effect. Since then, real air fares never rose above this maximum (see Fig. 3) and there is no variation in the $FARE^{max}$ series. As such the statistical insignificance of the hysteresis effects could simply be a manifestation of the limitations in data. We note that despite the limitations of the $FARE^{max}$ series, there is still evidence of a difference between β_{max} and β_{fall}.

Model 2 has jet fuel prices instead of air fare as an explanatory factor. There is evidence of imperfect reversibility with respect to fuel prices as well, as the Wald F statistic is 8.91 for the equality test of γ_{max}=γ_{rec}=γ_{fall}. Independently, there is evidence of both asymmetry (F statistic for γ_{rec}=γ_{fall} is 7.52) and hysteresis (F statistic for γ_{max}=γ_{rec} is 17.38). There is also no statistically significant effect on air transport demand when jet fuel prices fall. These findings support Wadud's (2014) earlier work on the asymmetric impacts of jet fuel prices. The imperfect reversibility with respect to fuel prices possibly results from behavioural as well as imperfectly reversible price transmission effects.

Intuitionally, air fare elasticities should be larger in magnitude than fuel price elasticities as air fare is a direct factor affecting air transport demand, while fuel prices affect demand indirectly through air fare. Eq. (4) also allows an understanding of this pattern of elasticities a priori. Both the elasticities of air transport demand with respect to fuel price and air fare are generally less than unity and negative (Department for Transport 2013, Bhadra 2012, Wadud 2011). Elasticity of air fare with respect to fuel prices is expected to be positive, but less than unity as fuel prices make up only a share of the air fare and there could be supply side operational options to cushion the effects of fuel prices. Under these circumstances the elasticity of air transport demand with respect to fuel prices should be smaller than the elasticity with respect to air fare. This is what we find in our estimation results too: elasticities of demand with respect to fuel prices are all statistically smaller in magnitude than corresponding elasticities with respect to air fare for all three decompositions of the air fare and fuel price series ($\chi^2(1)$=3.99, 27.04 and 26.14 for maximum, recovery and fall series respectively). We also note that the model with air fare (Model 1) performs better than the model with jet fuel prices (Model 2) through the goodness of fit statistics such as the adjusted R^2, AIC or BIC.

Eq. (4) can also be used to understand the presence or absence of asymmetry in price transmissions. Table 4 presents the calculated elasticity of air fare with respect to the three fuel price decompositions. It suggests that the air fare increases the most with respect to an increase in the fuel price if the fuel price rise goes above the previous maximum. Air fare also increases with respect to price recoveries below the maximum price, but this elasticity is smaller, indicating the presence of hysteresis. The large hysteresis effects of jet fuel price on air transport demand ($\gamma_{max}/\gamma_{rec}$≈7) appears to be driven by a large hysteresis effect in price transmissions to air fare ($\delta_{max}/\delta_{rec}$≈4.2), and a rather small hysteresis effect of the air fare itself ($\alpha_{max}/\alpha_{rec}$≈1.6).

[Table 4]

Results from Tables 1 and 4 also show that the elasticity of air fare during a reduction in fuel price is statistically not different from zero, i.e. there are no significant effects on air fare during falling jet fuel prices. This suggests the presence of asymmetric effects during cost transmission from jet fuel costs to air fare. Our results therefore agree with Escoberi (2013), who found evidence of asymmetry in cost pass-through in airlines. Especially, Escoberi (2013) reported no effects on airline prices when the (capacity) costs fall, a result similar to our finding as well. Our results also agree with a wider literature on asymmetry of price transmission, e.g. from crude oil to gasoline (Bacon 1991, Borenstein et al. 1997). Table 5 presents the summary conclusions for the imperfect reversibility of air transport demand and of cost pass-through qualitatively.

[Table 5]

7. Conclusions

This paper sets out to investigate if air transport demand is perfectly reversible or not. We find statistical evidence of imperfect reversibility for the effects of income, fuel price and air fare on revenue passenger enplanement in the USA. As in Wadud (2014), we find the presence of both asymmetry and hysteresis in the effects of income and fuel price on air transport demand. In addition, we conclude that air fare has a statistically significant asymmetric effect on aviation demand. Although this difference between the demand responses to a rising and falling air fare is numerically very small, it is not trivial in relative terms. Statistical evidence pointed to an absence of hysteresis effects of air fare, yet we believe that the results for hysteresis effects is inconclusive, given air fare continued to fall during our sample period barring few initial years, which makes it difficult to obtain statistical significance. Nonetheless, there is clear evidence on the presence of asymmetry and hysteresis in air transport demand which calls into question the appropriateness of the reversibility assumption in traditional air transport demand models of the past.

One of our major objectives was to have a deeper understanding of the reversible or imperfectly reversible effects of air fare and fuel price. We find that the elasticities of air transport demand with respect to air fare are larger than that with respect to fuel price for all three decompositions of air fare and fuel price. The comparison of the effects of air fare and jet fuel price also allows us to infer the reversibility of cost pass-through from jet fuel prices to air fare. There is evidence that air fare responds more to a fuel price increase above a previous maximum than to a sub-maximum increase in fuel price, which is an example of hysteresis effect in cost pass-through. We also find that falling fuel prices have no statistically significant effect on air fare providing evidence on asymmetric cost pass-through. This indicates that air transport passengers do not immediately benefit from a fall in jet fuel prices. In such a case, regulatory oversight may be required in order to ensure that the benefits from falling jet fuel prices are passed on to the consumers. The asymmetry in fuel cost pass-through also hints at the possibility of asymmetry in passing through the costs of carbon permits if a global aviation emissions trading scheme is set up.

The presence of imperfect reversibility in demand functions can have important policy implications. For example, demand responses to any policy measure that increases the air fare or fuel price would likely be underestimated if a reversible demand function is assumed, which could skew decisions about policy choices to reduce carbon emissions from aviation. Also, the hysteresis effects of fuel price on demand means that the effect of any policy that directly increases fuel prices marginally (i.e. sub-maximum) would be overestimated if fuel price elasticity from a reversible model are used, again biasing policy decisions. In fact, we find that changes in air travel demand is quite small for fuel price increases below the previous maximum fuel price, indicating policies affecting fuel prices marginally in order to manage demand could be ineffective. Another policy and planning recommendation is to target air fare directly, rather than fuel prices if demand needs to be managed. Our results also indicate that large increases (above previous-maximum) in fuel prices or air fare could have disproportionately larger demand impact as compared to a small increase (below previous-maximum). On the other hand, the hysteresis effects of income imply that the air transport demand rebounds quicker after a recession as compared to the overall long run increases in demand. This can be important for short- term decisions such as airline revenue management, choice and frequency of flights or airport planning and operations during and after an economic recession.

Our aggregate analysis still has some limitations. Air transport market is substantially segmented in terms of travel purpose, travel class, travel distance, origin-destination characteristics, presence and type of competition, business models (low cost vs. legacy), etc. Therefore, the asymmetry and hysteresis effects are likely to show substantial heterogeneity depending on these various market types. Especially, the ability of the airlines to pass the fuel costs on to the passengers depends on the competition in the market (Winston and Morrison 1997). It is also not entirely implausible that a strong imperfect reversibility in one market type overcomes a symmetric relationship in another to result an overall imperfectly reversible relationship. An aggregate measure such as ours may mask some of these differences, yet the modelling framework can still be applied if such market level data become available. Future work using US DB1B or similar data for individual itinerary or panel data for different countries, regions or markets could provide useful insight in this regard. Future studies should also investigate the effects of fuel price hedging which can substantially affect price transmission and subsequently demand responses to fuel prices. While our dataset was for the USA, we believe such imperfect reversibility is likely to hold in other mature airline markets as well and extension of the work in other countries will be interesting too.

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Tables

Table 1. Parameter estimates for the econometric model

	Model 1-air fare		Model 2-fuel price	
	Parameter	t-stat	Parameter	t-stat
$RPEN$ lag 1	0.596***	18.64	0.607***	19.48
$RPEN$ lag 12	0.132***	4.87	0.112***	4.08
Y^{max} (income, max series)	0.156***	2.35	0.370***	4.9
Y^{rec} (income, cum. recovery series)	0.826***	7.37	0.716***	6.38
Y^{fall} (income, cum. fall series)	0.635***	5.22	0.436***	3.23
$FARE^{max}/P^{max}$ (fare or price, max series)	-0.229***	-3.77	-0.097***	-4.87
$FARE^{rec}/P^{rec}$ (fare or price, cum. recovery series)	-0.143***	-5.43	-0.014***	-3.33
$FARE^{fall}/P^{fall}$ (fare or price, cum. fall series)	-0.113***	-4.91	-0.001	-0.1
U (unemployment)	-0.039***	-2.98	-0.004	-0.28
D_1 (air traffic controller strike)	-0.076***	-2.98	-0.071***	-2.79
D_2 (9-11 shock effect)	-0.403***	-15.94	-0.414***	-16.38
D_3 (9-11 sustained effect)	-0.019***	-3.32	-0.023***	-3.81
D_4 (thanksgiving in December)	0.080***	6.05	0.078***	5.92
MD_2 -Feb	0.101***	15.08	0.103***	15.37
MD_3 -Mar	0.156***	20.98	0.159***	21.44
MD_4 -Apr	0.073***	10.18	0.077***	10.58
MD_5 -May	0.070***	10.42	0.075***	10.86
MD_6 -Jun	0.157***	19.12	0.159***	19.53
MD_7 -Jul	0.115***	12.6	0.117***	12.94
MD_8 -Aug	0.114***	12.44	0.117***	12.83
MD_9 -Sep	-0.030***	-3.9	-0.028***	-3.62
MD_{10} -Oct	0.099***	15.21	0.104***	15.73
MD_{11} -Nov	0.054***	8.57	0.057***	8.9
MD_{12} -Dec	0.051***	7.9	0.054***	8.32
$Constant\ (\mu)$	0.194	0.24	-3.380***	-4.58
<u>*Diagnostic tests*</u>				
N	408		408	
Adj-R^2	0.9878		0.9877	
AIC/BIC	-1840/-1739.76		-1837.17/-1736.89	
Dicky-Fuller GLS unit root test for stationarity of long run relationship	-3.154		-3.989	
Breusch-Godfrey test for autocorrelation	0.031 (p=0.86)		0.020 (p=0.89)	
Durbin's h test for autocorrelation	0.029 (p=0.86)		0.019 (p=0.89)	
Shapiro-Wilk test for normality of residuals	0.157 (p=0.44)		1.24 (p=0.10)	
Bartlett's white noise test of residuals	1.173 (p=0.13)		1.22 (p=0.10)	

Table 2. Short-run and long run demand elasticities with respect to price and income

	Model 1 (air fare)		Model 2 (fuel price)	
	Short-run	Long-run#	Short-run	Long-run#
Y^{max}	0.156**	0.574***	0.370***	1.313***
Y^{rec}	0.826***	3.041***	0.716***	2.542***
Y^{fall}	0.635***	2.339***	0.436***	1.549***
$FARE^{max}$ / P^{max}	-0.229***	-0.843***	-0.097***	-0.344***
$FARE^{rec}$/P^{rec}	-0.143***	-0.526***	-0.014***	-0.051***
$FARE^{fall}$/P^{fall}	-0.113***	-0.417***	Insig.	Insig.

#long run parameter = $(\alpha$'s or β's or γ's$)/(1-\omega_1-\omega_{12})$ from Eq. (8) or (9)

Table 3. Hypothesis tests for imperfect reversibility

	Model 1 (air fare)		Model 2 (fuel price)	
Test restrictions	F-statistic	p-value	F-statistic	p-value
$\alpha_{max} = \alpha_{rec} = \alpha_{fall}/\alpha'_{max} = \alpha'_{rec} = \alpha'_{fall}$	18.63***	0.00	9.78***	0.00
$\alpha_{rec} = \alpha_{fall}/\alpha'_{rec} = \alpha'_{fall}$	8.03***	0.00	11.67***	0.00
$\alpha_{max} = \alpha_{fall}/\alpha'_{max} = \alpha'_{fall}$	14.53***	0.00	0.18	0.67
$\alpha_{max} = \alpha_{rec}/\alpha'_{max} = \alpha'_{rec}$	33.17***	0.00	7.20***	0.01
$\beta_{max} = \beta_{rec} = \beta_{fall}/\gamma_{max}=\gamma_{rec}=\gamma_{fall}$	5.37***	0.00	8.91***	0.00
$\beta_{rec} = \beta_{fall}/\gamma_{rec}=\gamma_{fall}$	7.54***	0.00	7.52***	0.01
$\beta_{max} = \beta_{fall}/\gamma_{max}=\gamma_{fall}$	3.94**	0.05	17.80***	0.00
$\beta_{max} = \beta_{rec}/\gamma_{max}=\gamma_{rec}$	2.17	0.14	17.38***	0.00

Table 4. Imperfect reversibility of cost pass-through

	Demand elasticity wrt air fare (β)	Demand elasticity wrt fuel price (γ)	Air fare elasticity wrt fuel price (δ)
Maximum series	-0.229***	-0.097***	0.423***
Sub-maximum recovery series	-0.143***	-0.014***	0.100***
Fall series	-0.113***	Insig.	Insig.

Table 5. Summary conclusions on imperfect reversibility

	Air transport demand			Air fare		
With respect to ..	Asymmetry	Hysteresis	Overall	Asymmetry	Hysteresis	Overall
Income	Yes	Yes	Yes			
Fuel price	Yes	Yes	Yes	Yes	Yes	Yes
Air fare	Yes	No?	Yes			

? may be affected by a lack of variance in the $FARE^{max}$ series.

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Figures

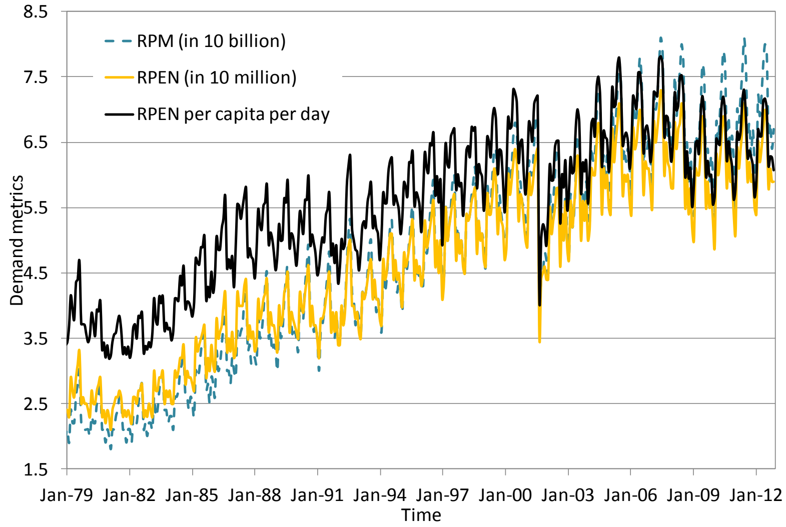

Fig. 1 Evolution of RPM, RPEN, RPEN per capita, and RPEN per capita per day

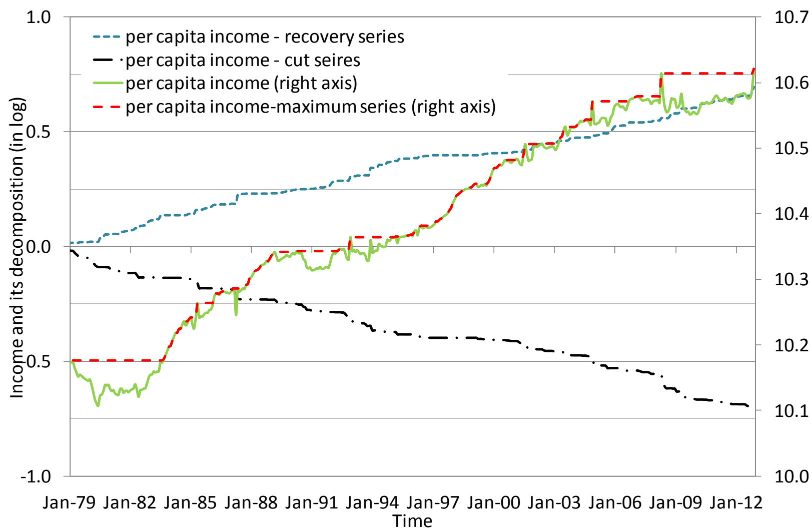

Fig. 2 Evolution of logarithm of real per capita disposable income and its three decompositions

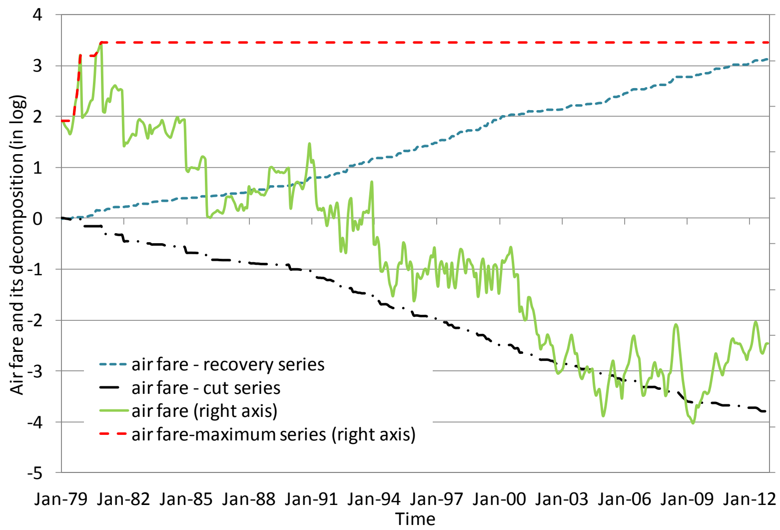

Fig. 3 Evolution of logarithm of real air fare and its three decompositions

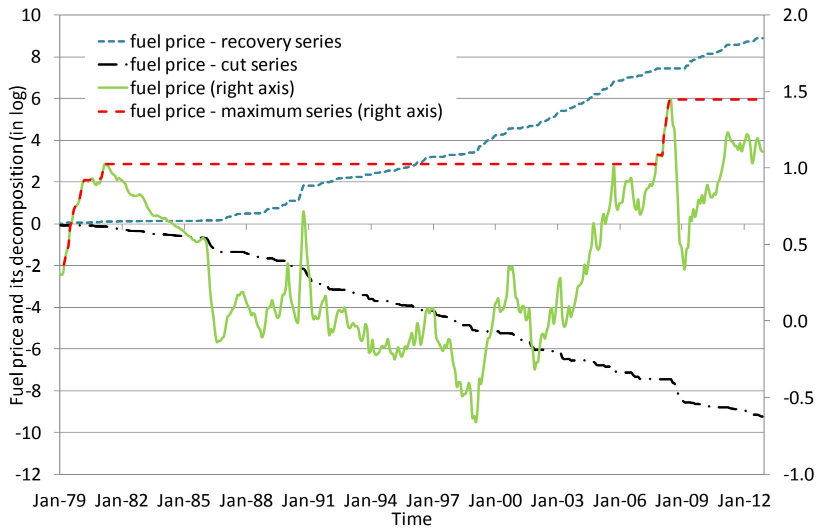

Fig. 4 Evolution of logarithm of real fuel price and its three decompositions