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Simultaneous Modeling of Passenger and Cargo Demand at an Airport

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Abstract

Forecasts for future passenger and cargo demands are important parameters for airport planners. While there are a number of studies for passenger demand in an airport, the number of studies for air cargo is much smaller. Also, these two entities are often separately dealt with in the literature. However, there can be advantages in modeling them both simultaneously, especially when time-series data is used for the estimation of the demand models. We follow a Seemingly Unrelated Regression (SUR) framework to jointly model passenger and cargo demand at the Shahjalal International Airport at Dhaka, Bangladesh. Allowing for contemporaneous correlation among the air passenger and air cargo demand models in the SUR approach allows a more efficient and reliable estimate than OLS and individual cointegration methods. We use the results of our simultaneous demand modeling to forecast passenger and cargo demand at the airport up to 2030.

Key Words

Passenger demand, air freight/cargo demand, econometric model, seemingly unrelated regression, cointegration

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INTRODUCTION

Forecasts for future passenger and cargo demand in an airport are an important parameter for airport planners, both for operational and strategic decision purposes. While short turn forecasts suffice for immediate operational planning, longer run forecasts are necessary for strategic decisions involving larger investments, e.g. for airport expansion or new airport construction projects. Future demand for aviation services is also an important parameter in the context of energy consumption and greenhouse gas emissions from this sector. There is a large body of literature on modeling passenger demand at a country or city (airport) level which utilizes aggregate time series, cross-sectional or panel information (and, in the past decade, disaggregate data as well). These studies use a variety of explanatory factors to explain passenger demand. On the other hand, there are only a few studies on cargo demand for airports (excluding integrated transport demand models). Separation of these two strands of literature can cause a loss of information especially when using time series data, as some of the explanatory factors that are not observed by the researcher can affect both passenger and cargo demand. In developing countries, where obtaining reliable data is a perennial problem, aggregate time series data is relatively reliable, and it will be very useful if the information in the time series data can be utilized as efficiently as possible. In this paper, we develop an econometric model for air passenger and cargo demand in Dhaka, Bangladesh, allowing for cross-correlations in the Seemingly Unrelated Regression (SUR) framework. To our knowledge, this is the first application of such an approach in simultaneously modeling air passenger and cargo demand at any airport. We also test for cointegration to ensure that possible non-stationarity of the time series variables are appropriately treated in the econometric model. In addition to the methodological improvement through simultaneous modeling of demand, we use the model to provide forecasts of passenger and cargo demand at the major international airport in Bangladesh. Reliable demand forecasts have become very important in the policy context because of the ongoing debate on the necessity of a new airport in Dhaka.

AIR PASSENGER AND CARGO IN BANGLADESH

There are currently eight airports in operation in Bangladesh - three international and five domestic. Despite the very short domestic travel distances in this small country (less than 30 minutes), the domestic airports could be sustained because of a lack of bridges over the many rivers that crisscross the country making road and rail travel time-consuming and cumbersome. Large investments in bridge construction have improved surface transportation over the years and as such majority of the domestic airports lost their patronage significantly. On the other hand, the international airports showed an opposite trend as the passenger patronage at the two airports in Dhaka and Chittagong continues to grow (Fig. 1). Similarly, air cargo handled in Dhaka and Chittagong continues to grow, but at the domestic airports, there is an opposite trend.

[Fig 1 here]

Dhaka is the capital of Bangladesh and centre of all economic, administrative and commercial activities of the country. Accordingly, Hazrat Shahjalal International Airport (HSIA), the airport serving the city, is the busiest of all (Fig. 1). In 2010, HSIA served 83% of air passengers and 89% of air cargo in Bangladesh. Since Dhaka is the major international gateway to the country, international passengers constitute the major share of HSIA's traffic. Backed by a strong GDP growth, international travel from the country has increased significantly and construction of a new airport has been on the national political agenda for the past few years. Forecasting demand is therefore of vital importance, both for the decision about a new airport as well as for planning the facilities for a new airport or an expansion of the existing airport.

LITERATURE ON AIR PASSENGER AND CARGO DEMAND

The Transportation Research Board (1), in its synthesis of aviation activity forecasting methods for US airports, find four general approaches to model and forecast airport specific demand. These are:

- Market share forecasting
- Econometric modeling
- Time series modeling
- Simulation modeling

Simulation modeling is used for detailed planning for airport operations and is not relevant here. Market share forecasting is primarily relevant to airline operators rather than national/city level policymakers interested in the feasibility of an expansion or new airport project. Econometric and time series modeling are the most relevant approach for our work as we have time series data for some of the explanatory factors that explains air travel demand. We also do not differentiate between econometric and time series modeling. We review the literature on those studies which uses time series (or cross-sectional time series/panel) data and utilizes econometric or time series modeling approaches (we also add a few studies on tourism demand forecasting which use time series data, but do not include disaggregate demand models as per Ortuzar and Simonetti (2)). Table 1 summarizes the salient features of the models using time series and panel data only.

Although the econometric model specifications in Table 1 often do not specifically mention the use of gravity models, where the travel demand between a city/country *pair* is dependent on some attraction and impedence factors between the pair (see (3) for a brief review of gravity models), all of these econometric models are gravity models in essence. For those studies where the demand is not explicitly for a city/country pair as in gravity models, and rather for one city/country, there is an underlying assumption that the explanatory characteristics for the other half of the pair remain *relatively* constant during the modeling (and forecasting) period.

[Table 1 here]

The review reveals that a wide range of explanatory factors have been used by the researchers to model air travel demand. These include GDP, income, air fare, exchange rates, travel time, population, export and import, aircraft movements, frequency of flights etc. The most important among these are the GDP or income which represents the size of the economic activity in a country. For a developing country like Bangladesh, GDP or per capita GDP also represents the ability of people to fly. Population is also an important variable as it explains the potential pool of air travelers. Although population data is often one of the most readily available information in most countries, it is often omitted from the list of explanatory factors. The reason, we conjecture, is primarily statistical: population data is often very highly correlated with GDP or per capita GDP data making estimation difficult. In the context of a gravity model population and GDP both represent an attraction factor.

Airfare, cost per km or price of jet fuel - all represent the deterrence to fly and generally have negative parameter estimates if included in the demand model. Price elasticities have always been an important parameter for researchers and policymakers alike, and there are a significant number of studies that estimate this parameter. Price elasticities can also vary depending on the trip purpose with business travel being less elastic (4). Dargay and Hanly (5) found that exchange rate and relative consumer price levels between countries/cities have larger influence on air travel demand than air fares alone. Profillidis (6) used exchange rates alone for air travel demand at Rhodes since it is primarily a leisure destination (exchange rates dictate if the destination is relatively expensive or not).

The log-log functional specification is the most common one for air travel demand models - apart from three, all studies follow this specification. Logarithmic conversion of the dependent and independent variables generally reduce potential heteroskedasticity in data and also allows direct interpretation of elasticities. Time series data are generally aggregated in nature, and it is no surprise that all of these studies use aggregated data, although the spatial coverage of aggregation can be different (city/country/region). A number of studies had a panel dataset but did not treat the panel nature of data and rather focused on individual time series for each of the cross-sections within the panel (5, 7-8).

A significant number of the demand models in Table 1 do not explicitly treat the time dimension of the data, despite the underlying data being time series in nature (6, 8-12). Wadud (3), DfT (4), BTCE (7), Tsekeris (13) and Cheze et al. (14) specifically utilize the time series properties of data in a multivariate dynamic setting while Andreoni and Postorino (15), Fernandes and Pacheco (16), Kulendran and King (17), Lim and McAleer (18) and Lim et al. (19) use univariate or multivariate time series models (mostly ARIMA or ARIMAX). In addition to traditional parametric econometric and time series techniques, a few novel techniques were used by researchers to estimate the models. For example, BaFail (8) and Alekseev and Seixas (12) used Artificial Neural Networks (ANN) while Profillidis (6) used fuzzy regression techniques to forecast passenger demands. However, there is no consensus that these alternate techniques are superior to the econometric models.

The number of studies using time series data for modeling air cargo transport demand is small compared to air passenger demand (20-23). This reflects the importance of air passenger demand with respect to cargo demand in most of the airports in the world. Since economic activity is the major driver of air cargo movements, GDP appears as an explanatory factor in all of these cargo demand models. In addition, a few include air fare or relative air fare (20). None of these studies use a pure univariate time series approach for forecasting air cargo demand although univariate models are fairly common for air passenger demand. Most of the cargo models do not explicitly treat the time series nature of data, too (20-22). Also, none of these studies of air cargo demand have any cross-sectional information.

Univariate ARIMA models, while extensively used for forecasting, is not particularly suited for long term forecasts or for conducting sensitivity of the forecasts to the potential explanatory factors. Carson et al. (24) also indicates that models with explanatory factors had better out-of-sample forecast performance for US air passenger demand. We therefore opt for a multivariate setting where demand can be expressed as a function of the explanatory variables, with specific attention to the time series aspect of data and further attention in the efficiency of estimation through joint estimation of both passenger and cargo demand.

DEMAND MODEL IN THIS STUDY

Model Specification

Following our review above, we include GDP as the primary explanatory variable in both our passenger and cargo demand models. The second explanatory variable is crude oil prices (COP). Although fuel prices constitute only a portion of air fare and the share of fuel prices in air fare also changed over the last three decades, we do not have access to any time series information on average air fares in Bangladesh. However, we believe that crude oil prices will capture at least some of the variations in air fare over the years.

Our third explanatory variable is the ratio of Purchasing Power Parity (PPP) conversion factor for GDP to market currency exchange rate. The ratio, known as National Price Level (NPL), compares the cost of a bundle of goods across different countries. More precisely, it reflects how many dollars are needed in Bangladesh to buy a dollar's worth of goods as compared to the United States. NPL should affect the foreign travel of Bangladeshis or foreigners' travel to Bangladesh due to the relative changes in the costs of travel brought about by the changes in NPL, but should not impact cargo demand. Therefore we include NPL in our passenger demand model only (and test its exclusion in the cargo model later).

Following literature, we utilize the constant-elasticity Cobb-Douglas functional form. Thus, our parameter estimates represent the elasticities of passenger or cargo demand with respect to the variables. Our conceptual specifications in the reduced form are:

$$PASS_t = \alpha_p (GDP_t)^{\beta_p} (COP_t)^{\gamma_p} (NPL_t)^{\delta_p} \quad \text{....} \quad (1)$$

$$CAR_t = \alpha_f (GDP_t)^{\beta_f} (COP_t)^{\gamma_f} \quad \text{....} \quad (2)$$

Where, $PASS$ = annual passenger at the airport in year t

CAR = annual cargo handled at the airport in year t

GDP = GDP of the country in year t

COP = Crude oil prices in year t

NPL = National price level in year t

α, β, γ and δ are the parameters to be estimated, and subscripts p and f represent passenger and cargo respectively. A priori, we expect parameters β to be positive (demand increases with an increase in GDP) and γ to be negative (demand decreases with an increase in crude oil prices). For a country which is a popular tourist destination, δ should be negative as traveling to the country becomes relatively more expensive as NPL increases. On the other hand, for a country which has more citizens traveling abroad than traveling into, δ should be positive. Bangladesh is not a popular tourist destination (e.g. like Nepal or Maldives) and therefore would likely fall in the second category.

Data

Annual passenger and cargo handled in HSIA in Dhaka is available from Statistical Year Books of various years, published by Bangladesh Bureau of Statistics (BBS, 25-28). Annual GDP and NPL were collected from the World Development Indicators database (29). Crude oil prices were collected from BP Statistical Review of World Energy (30). GDP, COP and NPL are all real values, i.e. in constant USD, chained to a specific year. The dataset is from 1982 to 2010.

Fig. 2 presents the evolution of the variables over the years. Clearly, there is an outlier in each of passenger and cargo data, year 2005 for passenger and year 1995 for cargo handled. Discussions with air transport professionals indicate that the outliers are not real data points and represent errors in reporting or data logging. Such discrepancies are not uncommon in data in the developing countries where data collection methods are not robust enough. The occurrence of these outliers requires us to add dummy variables for corresponding years in the relevant demand models ($D05$ for passenger demand in Eq. 1 and $D95$ for cargo demand in Eq. 2).

[Fig 2 here]

Model Estimation

Although Ordinary Least Squares (OLS) was used in many of the studies reviewed above, OLS is often not appropriate for time series data, especially when there is significant autocorrelation or moving average terms in the errors of the estimation equation. Also, the non-stationary nature of some of the time series data can have important implications in regression properties. If two time dependent variables follow a common trend that causes them to move in the same direction, it is possible to find a good correlation among them despite not having a *true* association. This can result in spurious regression and unreliable parameter estimates. However, it is also possible that the two non-stationary variables are evolving together in time in the long run, a phenomenon known as cointegration, and in such case OLS estimation and the resulting parameter estimates are valid.

If the variables are cointegrated, then the Engle-Granger's (31) two step regression allows estimation of the long run relationship through a static OLS model, followed by an Error Correction Model (ECM) for the short run parameter estimates. With our conceptual model specifications in Eq. 1 and 2, taking logarithms of both sides, our estimation equation for the long run becomes (ignoring the dummies):

$$lnPASS_t = \alpha_p + \beta_p lnGDP_t + \gamma_p lnCOP_t + \delta_p lnNPL_t + \xi_{p,t} \quad .... \quad (3)$$

$$lnCAR_t = \alpha_f + \beta_f lnGDP_t + \gamma_f lnCOP_t + \xi_{f,t} \quad .... \quad (4)$$

If the variables in Eqs. 3 and 4 are cointegrated, their combination will be stationary and thus the residuals $\xi_{p,t}$ and $\xi_{f,t}$ will also be stationary. Therefore a straight-forward approach to testing whether the variables are cointegrated is to test if the regression residuals are stationary through the unit-root tests, such as the Dicky-Fuller Generalized Least Squares test (DF-GLS, by Elliott et al. (32)).

In a long run equilibrium, residuals ξ_p and ξ_f should be zero, however, at any given time t, demand is not in equilibrium (i.e. $\xi_{p,t}, \xi_{f,t} \neq 0$), and this disequilibrium is adjusted in the demand of the next time period. At the same time, the demand responds to the short term changes in the external explanatory factors. Thus the ECM becomes:

$$\Delta lnPASS_t = \mu_p + \sum_{j=1}^{l_p} \kappa_{p,j} \Delta lnGDP_{t-j} + \sum_{j=1}^{m_p} \lambda_{p,j} \Delta lnCOP_{t-j} + \sum_{j=1}^{n_p} \tau_{p,j} \Delta lnNPL_{t-j} + \omega_p \xi_{p,t-1} + \varepsilon_{p,t} \quad .... \quad (5)$$

$$\Delta lnCAR_t = \mu_f + \sum_{j=1}^{l_f} \kappa_{f,j} \Delta lnGDP_{t-j} + \sum_{j=1}^{m_f} \lambda_{f,j} \Delta lnCOP_{t-j} + \omega_f \xi_{f,t-1} + \varepsilon_{f,t} \quad .... \quad (6)$$

where the lags l, m and n are chosen such that the residuals ε_t are white noise. ξ_{t-1} is the disequilibrium from the previous time period. κ, μ, λ and τ are short run parameters corresponding to the explanatory variables, while ω represents the speed of adjustment to the disequilibrium. If the long run variables in Eqs. 3 and 4 are cointegrated, ω in the ECM will be negative and statistically significant.

The Engle-Granger's two-step process can be individually applied to estimate the long run and short run parameters for the passenger and cargo demand above. However, it is possible that the observed passenger and cargo demand have been affected in each period by some exogenous variables that are not observed (or unavailable to us) and therefore not explicitly incorporated within our model. Examples of such variables can be operational costs, key policy changes, airport operational improvements, natural disasters, etc. Any of these factors affects both the passenger and the cargo handled at the HSIA and omission of them from our models can give rise to contemporaneous correlation between the residuals of the two estimation equations. This means that the $E[\xi_{p,t}\ \xi_{f,t}]$ is no longer zero as it would have been if the two equations were independent. This is indeed a possibility and we correct for this by specifying a correlation between the errors of the two equations and estimating them simultaneously as a system, instead of two independent OLS estimations. We follow Zellner's (33) Seemingly Unrelated Regression (SUR) method which allows consistent and efficient estimation of the parameters of an equation system with across-equation correlation among the errors. SUR uses Feasible Generalized Least Squares (FGLS) technique to estimate the parameters. Such simultaneous solution of the passenger and cargo demand equations as a system allows the utilization of the full information potentially contained in the data as a whole and generally results in more efficient estimation of the parameters as compared to OLS. Even within the SUR framework, if the variables are not cointegrated, the results would still be spurious. Note that panel data techniques are not applicable here. This is because: a. it assumes that the impact of the explanatory variables (i.e. the estimation parameters) is the same on both passenger and cargo demand, which it should not be, and b. for panel models the dependent variables and explanatory factors are the same across different cross-sectional units, which is not our case either. This also eliminates the possibility of use of panel data unit root tests or panel data cointegration techniques.

Model Diagnostics

The first stage of estimation involves testing all relevant variables for their stationary or non-stationary characteristics through unit root tests. The traditional unit root tests, such as the DF-GLS, are biased toward rejection of non-stationarity in the presence of outliers in data, which is the case for our $lnPASS$ and $lnCAR$ variables. We therefore use Vogelsang's (34) approach, which accounts for the presence of additive outliers, to test the presence of unit root in these two series. For other variables we use the DF-GLS test. Since unit root test results are sensitive to the choice of lag length, and the choice of lag length itself is sensitive to the different techniques employed, we present in Table 2 the results of the unit root tests using three lag-choice methods: Ng-Perron's sequential t test, Schwarz's Bayesian Information Criteria and Akaike Information Criteria (AIC). All the variables in our model are non-stationary at level, stationary at first difference. The residuals of Eqs. 3 and 4 are also stationary, indicating the variables, although themselves non-stationary, are cointegrated and have a stable long run relationship, thus the OLS estimation is *not* spurious.

[Table 2 here]

Table 3 presents the results of the individual OLS estimates of the long run demand model for passenger and cargo. Parameter estimates for both types of demand have expected signs (GDP positive, COP negative), although the national price level (NPL) parameter is statistically insignificant even at 90% confidence level for the passenger demand model. The dummy variables indicating the two outliers are also statistically significant for both the models, justifying their inclusion. Table 3 also presents corresponding system estimates using SUR. The parameters are almost the same as the OLS estimates, but the standard errors of the SUR estimates are now reduced. This efficiency of SUR estimation now allows the NPL parameter for the passenger demand model to become statistically significant as well. This is a clear improvement over the OLS estimate, which would have wrongly concluded that NPL had no significant impact on passenger demand. Breusch-Pagan test for the independence of the cargo and passenger demand models (i.e. their errors are not correlated) is rejected at 99% confidence level, indicating that SUR estimation is indeed the preferred approach.

[Table 3 here]

The ECM for both models are also estimated using OLS and SUR (Table 4), where the Breusch-Pagan test again indicates cross-correlation of the residuals. The parameter estimates for the disequilibrium in the previous period is negative, less than unity, and statistically significant for both the models (-0.87 and -0.86 respectively for passenger and cargo), as it should be for cointegrated variables. SUR estimation again allows efficient estimation as the short run parameter estimate for crude oil price is now statistically significant, which it was not under the OLS estimation. Simultaneous estimation of passenger and cargo under the SUR framework thus is a clear improvement upon OLS estimations. Note that different model specifications with slightly different variables (e.g. GDP per capita, population, exclusion of dummies) have been tested, but none were better than our chosen model. Results for alternate specifications are available upon request.

[Table 4 here]

Discussions on Elasticity Estimates

Since our model is in a log-log form, the parameter estimates directly represent the elasticity of demand with respect to the variable. The long run income elasticity (GDP is used as a proxy for income) for air passenger demand is 1.36, which indicates air travel is a luxury good. Previous review by Gillingwater et al. (35) has also found that the income elasticity of air travel is generally above 1 and the recent DfT (4) study found an income elasticity of 1.3 for the UK. Wadud's (3) previous income elasticity for domestic air travel in Bangladesh was 1.24, indicating there is more demand for international travel than domestic travel as the income rises. This is not surprising as Bangladesh is a very small country, and domestic air travel is increasingly under competition with surface transportation as the bridges across the major rivers are being built and luxurious intercity buses operate directly to new destinations.

Elasticity of air travel demand with respect to crude oil price (COP) is -0.16. This appears to be on the lower side of -1.15, the mean elasticity found in Brons et al. (36) meta analysis, although DfT (4) finds that the UK leisure sector has an elasticity between -0.2 (foreign) and -1.0 (domestic). It is plausible that the price elasticity could be small since air travel in Bangladesh is either due to business purposes (which is less price elastic) or due to leisure travel by the highest income segment of the population, who are less sensitive to price. Also, our price elasticity is with respect to the price of crude oil and not with respect to the air fare, as in other studies. Crude oil price only forms a component of air fare and thus captures only a portion of the full price sensitivity of the air travelers. We expect the demand elasticity with respect to air fare in Bangladesh to be larger in magnitude than 0.16.

The long run impact of national price level (NPL) is 0.36 and positive, which possibly reflects that Bangladesh has more tourists (or migrants) traveling abroad than travelling in. An increase in the national price level improves the buying capacity of the Bangladeshis in another country and thus air travel abroad becomes more attractive. The relevant parameter in literature is Dargay and Hanly's (5) use of relative price level, which had an estimate for -0.77 (the negative was because their price level was for rest of the world relative to UK, ours is the opposite).

Long run income elasticity for air cargo at HSIA is 1.77, larger than that for passenger demand. Income elasticity for air cargo was 1.54 in a recent estimate for China (21), although another study reveals it is 9.35 in the USA (22). It is not clear why the income elasticity for the US by Chi and Baek (22) is so large, especially when Wang et al. (20) had found an income elasticity of between 1.35 and 1.81 in the USA, albeit with much older data. Boeing (37) also reports that the income elasticity of world air cargo is around 2. Our air cargo results thus agree with the majority of the literature.

Long run elasticity of air cargo with respect to crude oil prices is -0.47, which is larger than the price elasticity of passenger demand. This is possibly due to two reasons. Firstly, the crude oil prices constitute a larger share of the prices charged for air cargo, therefore COP reflects the actual prices better for air cargo than for passenger travel. Secondly, air cargo is possibly more price sensitive than passenger air travel in Bangladesh, as there are other cargo alternatives (e.g. maritime shipping), but for passenger air travel there are almost no substitute modes (besides traveling to India and Nepal by surface transport).

Short-run income, price and NPL elasticities from the ECM are 1.41, -0.09 and 0.41 respectively. While short run responses are generally smaller than long run responses, only price elasticity follows this norm here. However, it is not unusual to find a larger short run elasticity (shock effect) in demand studies (e.g. Puller and Greening (38) for gasoline demand). Also, although the short run elasticities appear larger for GDP and NPL, statistically they are not significantly different from the long run estimates. Our conclusion is that the demand responses to a change in income or national price level are fairly quick resulting in similar long run and short run elasticities.

Short run income elasticity for air cargo is the same as long run elasticity (both 1.77), while short run crude oil price elasticity (-0.21) is less than half that of long run price elasticity (-0.47). A parameter estimate of -0.86 for the residuals of previous time period means that 86% of the disequilibrium in air cargo demand in one period is adjusted during the following period.

PASSENGER AND CARGO FORECASTS

We use the long-run elasticity estimates to predict the passenger and cargo demand at the HSIA until 2030. The demand predictions are also conditional on the forecast explanatory variables themselves. We use three scenarios of projected GDP and crude oil price. The real GDP growths are assumed to be 5%, 6%, and 7% for our low, reference and high growth scenarios. For future crude oil price US Energy Information Administration's (EIA) projections in the Annual Energy Outlook (39), which also has low, reference and high price scenarios. The projected real GDP and real crude oil prices are presented in Fig. 3. In the absence of any guideline on how future price levels in Bangladesh will evolve with respect to that of the US, we kept the NPL variable at its 2010 value throughout the prediction period.

[Fig 3 here]

Figs. 4 and 5 present the predictions for passenger and cargo demand respectively. Instead of generating forecasts for all nine (3×3) combinations of GDP and crude oil price, we generate forecasts for three scenarios. The reference scenario is where both GDP and crude oil price are at their respective reference values. The high demand scenario reflects the conditions conducive to high aviation demand, i.e. high GDP and low prices, while the low demand scenario results from low GDP and high crude oil prices. While it is unlikely that actual demand will follow either of these two extreme cases, these two forecasts delineate the range within which the demand should remain in future. The shaded (light blue and textured) areas represent the prediction standard errors (assuming GDP and crude oil prices are deterministic) for SUR and OLS estimation. For passenger demand, SUR prediction errors are smaller, as expected. For cargo demand, the error bands are almost identical (although SUR error band is still numerically smaller than the OLS error band).

[Fig 4 here]

[Fig 5 here]

Reference case passenger demand at HSIA is expected to increase five folds from 4 million in 2010 to 20.1 million in 2030. The high demand and low demand scenario yields 30.9 and 15.2 million passengers respectively. Our high demand scenario therefore is twice as high as the low demand scenario. As a result of larger income elasticity, cargo demand increases even quicker than the passenger demand, despite a larger price sensitivity. Cargo demand in 2030 is expected to reach a million tons in the reference scenario, more than six folds increase over its year 2010 value. Cargo demands in the high and low demand scenarios are 2 and 0.6 million tons respectively.

CONCLUSIONS

Estimates of potential passenger and cargo demand in an airport are an important planning input, for both operational and strategic planning. We employed the Seemingly Unrelated Regression (SUR) framework to simultaneously model air passenger and cargo demand at HSIA in Dhaka, Bangladesh. The SUR framework utilizes the potential correlation among the residuals of the passenger and cargo demand models, which can easily arise in the time series context. Parameter estimates were not too different between SUR and OLS methods, but SUR resulted in more efficient estimations and allowed better inference as compared to the OLS. The efficiency of estimation aspect through SUR is important, since OLS estimation was leading to potentially wrong inference for some important explanatory variables. Thus, a joint modeling approach is beneficial in situations where large amount of reliable data is difficult to obtain and efficient estimation using existing data is important for proper inference and decision making. The method will therefore be especially useful to the practitioners in developing countries. Even in developed countries time series data is often used for forecasting and the joint modeling approach will improve upon individual modeling results.

Our results show that air cargo is more price and income elastic than air passenger demand at HSIA. The predicted passenger demand in 2030 in the reference scenario is 20.1 million per year, which is much larger than the current terminal capacity of 8 million, that the Civil Aviation Authority of Bangladesh expects in the next 20 years (40). Our forecast reveals that at the current GDP growth, the terminal capacity will possibly be exhausted before 2020. Cargo is expected to grow at an even larger rate. With a large lead time for construction of a new airport, especially in the context of site selection – which faced violent opposition from local people at few places near Dhaka already – it is very important to plan an extension of the current airport as an alternate strategy in order to meet the potential increase in demand in future.

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Figures

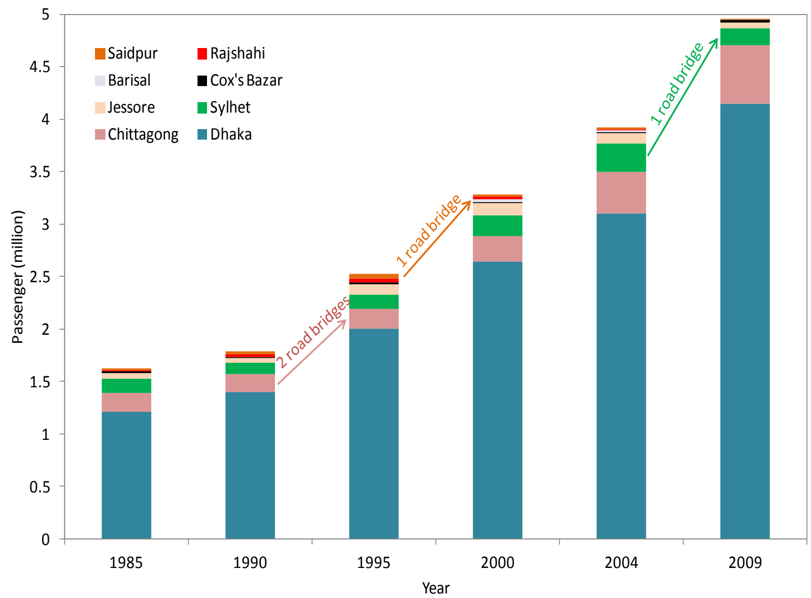

Fig. 1 Trend of passengers handled at the various airports in Bangladesh

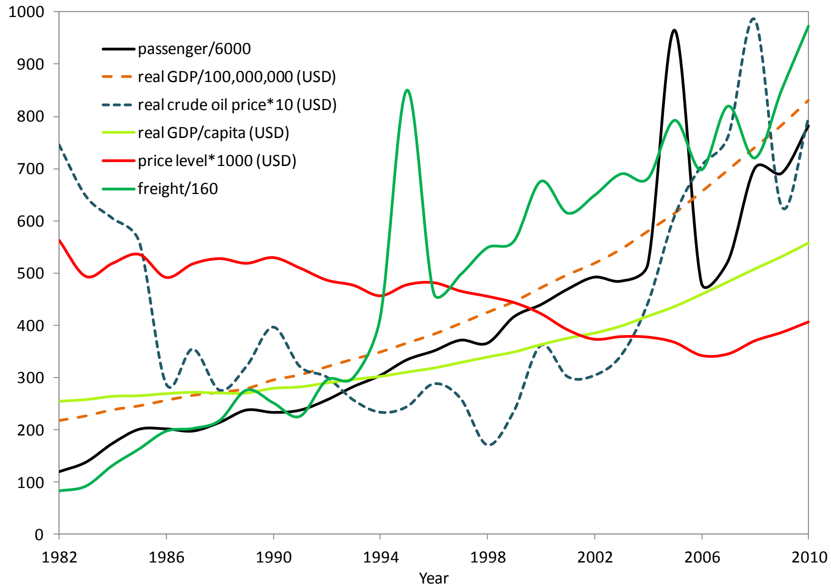

Fig. 2 Historical data on passenger, cargo, real GDP, real crude oil price, national price level

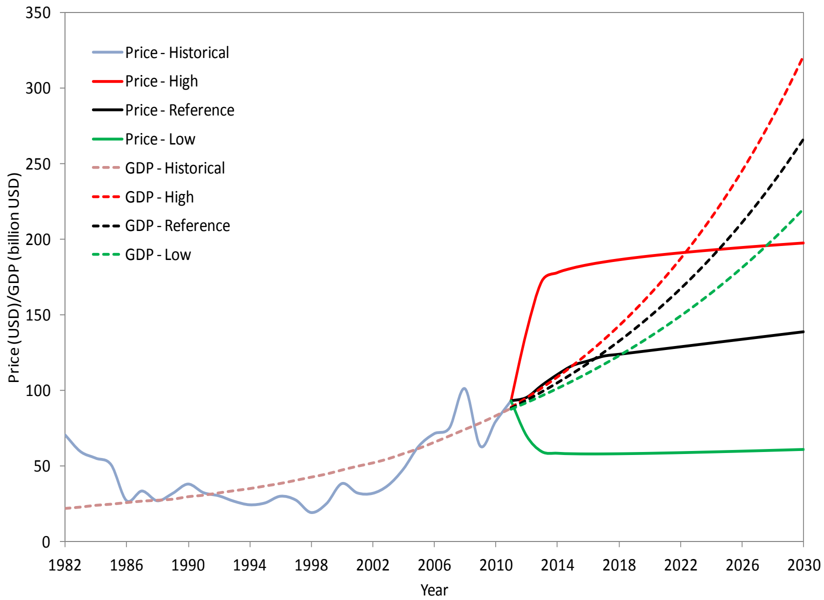

Fig 3. Projection of real GDP and real crude oil price underlying demand forecasts

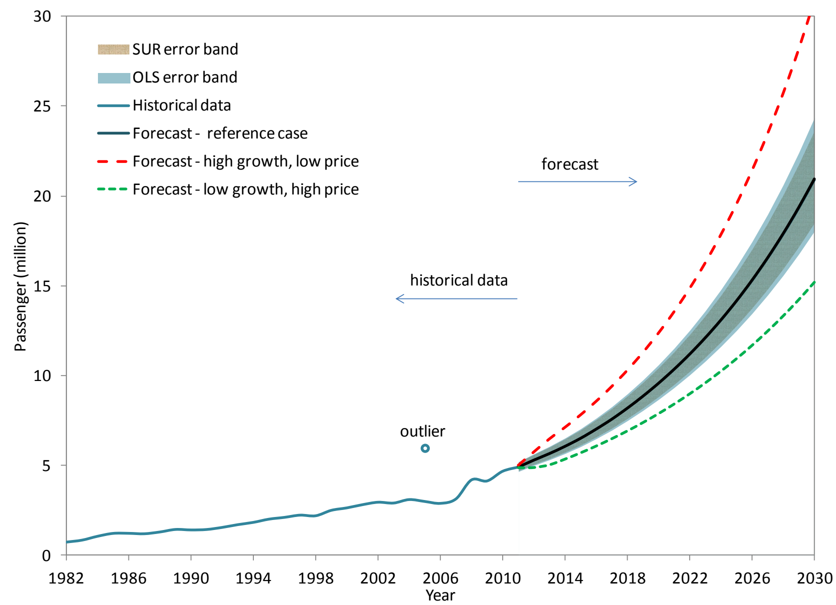

Fig. 4 Passenger demand forecast at HSIA

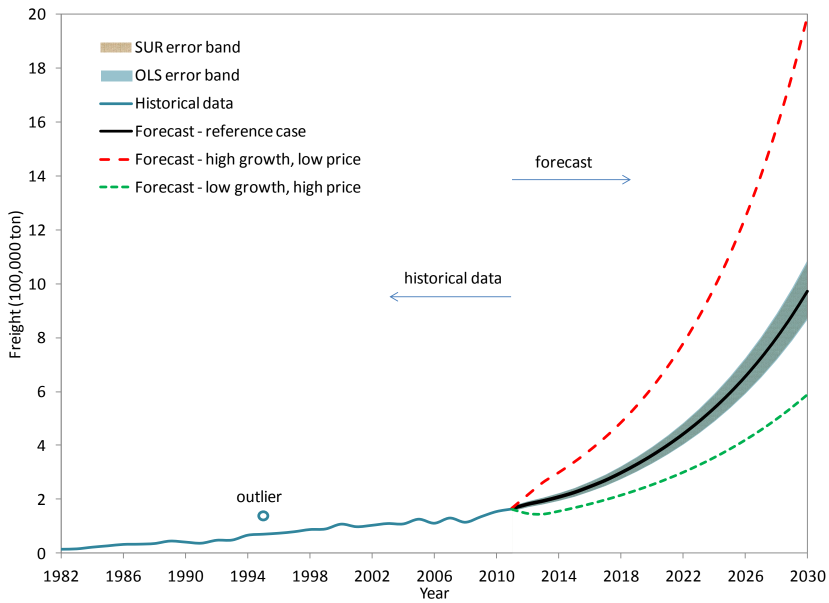

Fig. 5 Cargo demand forecast at HSIA

Tables

Table 1. Summary of selected studies for air travel demand that uses time series data

Study	City/ country	Explanatory factors	Data type	Functional form	No. of observations	Estimation method	Income/GDP elasticity*	Price/fare elasticity*
Air travel								
Wadud (3)	Khulna-Bangladesh	GDP per capita, ratio of air to road travel time population	cities, panel	Log-log	2 cities × 36 years	Fixed effect panel with AR errors	1.24	-
DfT (4)	UK	GDP of UK and abroad, consumer expenditure in UK, fares in UK and abroad, imports, exports, exchange rates	markets, panel	Log-log	21 markets × various lengths, 18 years max	ECM for each market	1.3	-0.5
Dargay and Hanly (5)	UK	Fare, per capita income, exchange rate, relative prices, per capita trade	countries, panel	Log-log	20 countries × 11 years	Dynamic for each country	1.05 to 1.8	-0.32 to -0.58
Profillidis (6)	Rhodes, Greece	Exchange rates	country, time series	Quadratic	22 years	OLS, fuzzy regression	-	-
BTCE (7)	Australia-international	GDP, Income, airfare, exchange rate	cities, panel	Log-log	2 markets × 24 cities × 32 quarters	Dynamic, for each market and city	0.21 to 11.58	-0.01 to -1.85
BaFail (8)	Saudi Arabia	GDP, CPI, per capita income, exchange rate, population etc.	cities, panel	Linear	5 cities × 18 years	ANN for each city	-	-
Alam and Karim (9)	Bangladesh	GDP and population of catchment, ratio of road to air travel time, dummy	cities, panel	Log-log	6 cities × 5 years	Pooled OLS	0.98	-
Abed et al. (10)	Saudi Arabia-international	Non-oil GDP, CPI, imports, population (best model)	country, time series	Linear	22 years	OLS	-	-
Abbas (11)	Cairo, Egypt	Population, foreign tourists	city, time series	Linear	11 years	OLS	-	-
Alekseev and Seixas (12)	Brazil	GDP, fare per km, dummy	country, time series	Log-log	20 years	OLS, ANN	1.45	-0.25
Tsekeris (13)	Greece-islands	GDP, population, tourism, relative frequency, time and capacity relative to ferries	islands, panel	Log-log	7 cities × 21 years	Dynamic panel-GMM	0.42 to 0.51	-0.15 to -0.23

Study	City/ country	Explanatory factors	Data type	Functional form	No. of observations	Estimation method	Income/GDP elasticity*	Price/fare elasticity*
Cheze et al. (14)	World	GDP, jet fuel price, shock dummies	regional, panel	Log-log	8 regions × 28 years	Dynamic panel-GMM	0.28 to 0.36 (short run)	-
Andreoni and Postorino (15)	Reggio-Calabria, Italy	Univariate; multivariate: income per capita, aircraft movements	city, time series	Log-log	16 years	ARIMA; ARIMAX	3.8§	-
Fernandes and Pacheco (16)	Brazil	Univariate	country, time series	Log	Not specified	Exponential smoothing	1.45	-0.25
Tourism								
Kulendran and King (17)	Australia-inbound	Univariate; multivariate: GDP/GNP, air fare	countries, panel	Log-log	4 countries × 64 quarters	ARIMA, ECM for each country	1.3 to 4.65	-0.64 to -2.89
Lim and McAleer (18)	Australia-inbound	Univariate	countries, panel	Log	3 countries × 60 quarters	ARIMA for each country	-	-
Lim et al. (19)	Japan-outbound	Income	countries, panel	Log-log	2 countries × 100 quarters	ARIMAX for each country	1.50 to 2.61#	-
Air cargo								
Wang et al. (20)	USA	GNP, unit yield for air and motor carriers	country, time series	Box-Cox transform.	28 years	OLS	1.35 to 1.81	-1.47 to -1.60
Jiang et al. (21)	China	GDP	country, time series	Log-log	13 years	OLS	1.54	-
Chi and Baek (22)	USA	GDP, price index	country, time series	Log-log	60 quarters	FM-OLS	9.35	-5.60
Chang and Chang (23)	Taiwan	GDP	country, time series	Log-log	33 years	Vector ECM	3.03	-

* For some of the studies, elasticities could not be calculated because of lack of information. #Excluding insignificant estimates for Taiwan. § Adding parameters of all lagged income variables.

OLS-Ordinary Least Squares, ARIMA-Autoregressive Integrated Moving Average, ARIMAX- Autoregressive Integrated Moving Average with Explanatory variables, ECM-Error Correction Model, GMM-Generalized Method of Moments, ANN-Artificial Neural Network, FM-OLS- Fully Modified Ordinary Least Squares

Table 2. Results of the unit root tests under different lag-choice methods (H_0: unit root exists)

Variables	NG-Perron sequential test		Schwarz Criteria		Modified AIC	
	Statistic (Chosen lag)	Critical value* (Conclusion)	Statistic (Chosen lag)	Critical value* (Conclusion)	Statistic (Chosen lag)	Critical value* (Conclusion)
Level						
$lnPASS$#	-4.70 (0)	-3.28 (S)	-2.96 (3)	-3.19 (NS)	-2.23 (8)	-3.09 (NS)
$lnCAR$#	-1.87 (4)	-3.17 (NS)	-2.63 (0)	-3.28 (NS)	-1.87 (4)	-3.17 (NS)
$lnGDP$	-1.69 (3)	-2.85 (NS)	-1.69 (3)	-2.85 (NS)	-0.98 (2)	-2.98 (NS)
$lnCOP$	-1.65 (0)	-3.07 (NS)	-0.77 (1)	-3.09 (NS)	-0.77 (1)	-3.09 (NS)
$lnNPL$	-2.18 (1)	-3.09 (NS)	-2.18 (1)	-3.09 (NS)	-2.18 (1)	-3.09 (NS)
Difference						
$\Delta lnPASS$#	-3.465 (0)	-3.28 (S)	-3.465 (0)	-3.28 (S)	-3.465 (0)	-3.28 (S)
$\Delta lnCAR$#	-6.31 (0)	-3.28 (S)	-6.31 (0)	-3.28 (S)	-6.31 (0)	-3.28 (S)
$\Delta lnGDP$	-3.60 (3)	-2.84 (S)	-3.16 (1)	-3.10 (S)	-3.16 (1)	-3.10 (S)
$\Delta lnCOP$	-4.68 (1)	-3.10 (S)	-4.68 (1)	-3.10 (S)	-4.68 (1)	-3.10 (S)
$\Delta lnNPL$	-3.39 (0)	-3.04 (S)	-3.00 (1)	-3.07 (S)[a]	-3.00 (1)	-3.07 (S)[a]
Residuals						
Eq. 3 – OLS	-4.36 (0)	-3.07 (S)	-3.79 (1)	-3.09 (S)	-3.79 (1)	-3.09 (S)
Eq. 4 – OLS	-5.04 (0)	-3.07 (S)	-4.67 (1)	-3.09 (S)	-4.67 (1)	-3.09 (S)
Eq. 3 – SUR	-4.52 (0)	-3.07 (S)	-4.24 (1)	-3.09 (S)	-2.69 (2)	-2.98 (NS)
Eq. 4 – SUR	-5.00 (0)	-3.07 (S)	-4.64 (1)	-3.09 (S)	-4.64 (1)	-3.09 (S)

* 10% critical values, # Vogelsang's (1999) approach, others are DF-GLS , S Stationary, NS non-stationary,

[a] Stationary at 15%,

Table 3. Engle-Granger static estimation of long run relationship

	OLS estimation		SUR estimation	
	$lnPASS$	$lnCAR$	$lnPASS$	$lnCAR$
$lnGDP$	1.370 (15.62)***	1.766 (29.68)***	1.364 (19.31)***	1.766 (31.97)***
$lnCOP$	-0.167 (-4.97)***	-0.467 (-8.77)***	-0.164 (-5.39)***	-0.469 (-9.53)***
$lnNPL$	*0.391 (1.61)*		*0.359 (1.90)**	
$D05$	0.626 (7.65)***		0.564 (8.86)***	
$D95$		0.728 (5.76)***		0.707 (7.04)***
Constant	-24.925 (-12.69)***	-30.370 (-21.62)***	-24.810 (-15.64)***	-30.368 (-23.28)***
Model diagnostics				
Adjusted R^2	0.978	0.971	0.981	0.974
Breusch-Godfrey LM test (H_0: no autocorrelation in residuals)	0.402 (p=0.526)	0.001 (p=0.980)	-	-
Breusch-Pagan test for independence of equations (H_0: no cross correlation)	-	-	7.788 (p=0.005)	
Number of observations	29	29	29	29

Table 4. Error Correction Model for passenger and cargo demand

	OLS estimation		SUR estimation	
	$\Delta lnPASS$	$\Delta lnCAR$	$\Delta lnPASS$	$\Delta lnCAR$
$\Delta lnGDP$	1.423 (5.50)***	1.773 (4.68)***	1.414 (6.22)***	1.774 (5.05)***
$\Delta lnCOP$	*-0.084 (-1.50)*	*-0.217 (-2.87)******	*-0.086 (-1.79)** *	-0.218 (-2.12)***
$\Delta lnNPL$	0.473 (1.85)*		0.413 (1.94)**	
$\Delta D05$	0.664 (14.19)***		0.625 (15.93)***	
$\Delta D95$		0.680 (9.77)***		0.673 (10.98)***
$\Delta\xi_{t-1}$	-0.777 (-4.06)***	-0.848 (-5.07)***	-0.873 (-5.53)***	-0.858 (-5.75)***
Model diagnostics				
Adjusted R^2	0.897	0.828	0.919	0.852
Breusch-Godfrey LM test (H_0: no autocorrelation in residuals)	1.741 (p=0.187)	0.201 (p=0.654)	-	-
Shapiro Wilk test (H_0: residuals are normally distributed)	W=0.97, V=0.77, z=-0.55(p=0.709)	W=0.95, V=1.49, z=0.82 (p=0.206)	W=0.97, V=0.83, z=-0.37(p=0.647)	W=0.95, V=1.50, z=0.83 (p=0.204)
Engle's LM test for ARCH (H_0: no ARCH effect in residuals)	1.176 (p=0.278)	0.246 (p=0.620)	-	-
Portmanteau Q test (H_0: residuals are white noise)	4.724 (p=0.967)	5.837 (p=0.924)	4.847 (p=0.963)	5.963 (0.918)
Breusch-Pagan test for independence of equations (H_0: no cross correlation)	-	-	2.741 (p=0.098)	
Number of observations	28	28	28	28