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DYNAMIC EFFECTS OF ECONOMIC GROWTH ON U.S. AIR PASSENGER AND FREIGHT SERVICES

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ABSTRACT

This paper examines the short- and long-run effects of economic growth and market shocks (e.g., 9/11 terrorist attacks, Iraq war, SARS epidemic, and 2008 financial crisis) on air passenger and freight services using an autoregressive distributed lag (ARDL) approach to cointegration. Results show that, in the long-run, both air passenger and freight services tend to increase with economic growth. In the short-run, however, only air passenger service is responsive to economic growth. Finally, only the 9/11 terrorist attacks and the SARS have detrimental effects on air passenger demand both in the short- and long-run, and in the long-run, respectively. However, those market shocks are found to have little impact on air freight demand.

INTRODUCTION

Growth in U.S. air transportation goes hand in hand with growth in the economy. Given that air transport is regarded as a normal good, income growth causes people to shift their demand towards faster modes of transportation, thereby resulting in increased demand for air transport (Ishutkina 2009). During the 1996-2010 period, for example, U.S. gross domestic product (GDP) per capita has increased by approximately 27%. Accordingly, during the same period, U.S. air passenger-miles for international and domestic travel have increased by approximately 52% and 32%, respectively (BTS 2012; BEA 2012). Since the U.S. economic recovery from the recent recession is likely to increase U.S. demand for air transport, it is very timely and important to examine the relationship between economic growth and air transport demand in the U.S.

Many studies have examined the economic growth-air transport demand nexus over the past decade. Earlier studies have typically relied on a static OLS model to tackle the issue (Ba-Fail et al. 2000, Petersen 2007, Karlaftis 2008). Ba-Fail et al. (2000), for example, analyze the determinants of air travel demand in the Kingdom of Saudi Arabia; they find a positive correlation between domestic air travel expansion and income growth. Similarly, Karlaftis (2008) investigates demand factors affecting passenger air service in Greece; he shows a significant income effect on domestic passenger traffic. Another body of the literature has emerged in recent years that concentrate on using a dynamic time-series model (Chang and Chang 2009, Marazzo et al. 2010, Cheze et al. 2011). Chang and Chang (2009), for example, adopt Granger causality to examine the causal relationship between air cargo expansion and economic growth in Taiwan. Marazzo et al. (2010) also apply Granger causality and impulse response analysis to investigate the relationship between air passenger demand and GDP in Brazil. They commonly show that economic growth plays a crucial role in promoting air transport demand. However, both Granger causality and impulse response analysis focus on short-run dynamics rather than long-run equilibrium relationships. Although some studies (Chang and Chang 2009, Marazzo et al. 2010) test the existence of long-run relationships among variables, they do not directly examine the mechanisms through which long-run equilibria restored. Furthermore, given that the short-run adjustment process of air industry in response to economic growth and/or market shocks could be remarkably different from the long-run process, it is crucial to incorporate both the short- and long-run dynamics in a model.

The objective of this paper is to conduct simultaneous analysis of the short- and long-run relationships between economic growth and air transport demand in the U.S. It is important to note that air transport services are generally comprised of passenger and freight services. In addition, unexpected market shocks (e.g., 9/11 terrorist attacks, Iraq war, SARS epidemic and 2008 financial crisis) may result in a change in U.S. air transport demand significantly. The special attention is thus given to examine the short- and long-run effects of economic growth and such market shocks as the 9/11 terrorist attacks, the Iraq war, the SARS epidemic, and the 2008 financial crisis (known as the great recession) on both air passenger and freight services. For this purpose, we employ the autogressive distributed lag (ARDL) approach – a new cointegration method developed by Pesaran et al. (2001). Since an error-correction model can easily be derived from the ARDL model through a simple linear transformation, this approach is widely adopted to estimate the short- and long-run parameters of the model simultaneously.

The outline of the paper is as follows. Section 2 provides details on the models, methodology, and data. The empirical results are discussed in Section 3 and concluding remarks are presented in section 4.

The Models and the Methodology

In analyzing the economic growth-air transport demand nexus in the U.S., the ARDL specifications for air passenger service (case I) and air freight service (case II) are specified as follows:

Case I:
$$\Delta \ln AP_t = a_0' + \sum_{k=1}^{p} a_1' \Delta \ln AP_{t-k} + \sum_{k=0}^{p} a_2' \Delta \ln Y_{t-k} + a_3' D_{911} + a_4' D_{recession}$$
$$+ a_5' D_{Iraqwar} + a_6' D_{SARS} + a_1 \ln AP_{t-1} + a_2 \ln Y_{t-1} + \zeta_t \qquad (1)$$

Case II:
$$\Delta \ln AF_t = b_0' + \sum_{k=1}^{p} b_1' \Delta \ln AF_{t-k} + \sum_{k=0}^{p} b_2' \Delta \ln Y_{t-k} + b_3' D_{911} + b_4' D_{recession}$$
$$+ b_5' D_{Iraqwar} + b_6' D_{SARS} + b_1 \ln AF_{t-1} + b_2 \ln Y_{t-1} + \eta_t \qquad (2)$$

where Δ is the difference operator; and p is lag order. In equations (1) and (2), it is assumed that the air passenger (AP_t) and air freight services (AF_t) depend positively on the U.S. real income (Y_t). In addition, to capture unexpected market shocks such as the 9/11 terrorist attacks, the Iraq war, the Severe Acute Respiratory Syndrome (SARS) epidemic, and the recent financial crisis over the sample period, four dummy variables – the 9/11 terrorist attacks (D_{911}) covering 2001:m9-2002:m6, the recent financial crisis ($D_{recession}$) covering 2008:m1-2011:m3, the Iraq war ($D_{Iraqwar}$) covering 2003:m3-2003:m5, and the SARS epidemic (D_{SARS}) covering 2002:m11-2003:m7 – are included in the estimation. Equations (1) and (2) are known as the error-correction version of the ARDL, because each equation incorporates the short-run dynamics (first-differenced variables) and the long-run equilibrium relationship (lagged-level variables). This specification is distinguished from the method of Engle and Granger (1987) in that a linear combination of lagged-level variables is used as a proxy for the lagged error-correction term. Pesaran et al. (2001) show that in this type of specification, the selected variables are said to be cointegrated if all the lagged-level variables are jointly significant in the equations. To test for this significance, an F-test with two sets of asymptotic critical values (upper and lower critical values) tabulated by Pesaran et al. (2001) can be conducted on equations (1) and (2). An upper critical value assumes that all the variables are $I(1)$, or nonstationary, while a lower critical value assumes they all are $I(0)$, or stationary. If the computed F-statistic falls above the upper bound of critical value, the selected variables are said to be cointegrated.

The main advantage of the ARDL over the standard cointegration methods (e.g., Engle and Granger 1987, Johansen 1995) is that it can be applied irrespective of their order of integration and therefore avoids the pre-testing problems. Further, the ARDL is proven to be more robust and performs better for small sample sizes than other cointegration techniques (Pesaran and Shin 1999, Panopoulou and Pittis 2004).

Monthly data that cover the period from January 1996 to March 2011 (1996:m1-2011:m3) are used to estimate equations (1) and (2). The data for U.S. air-passenger demand (in thousand passenger-miles) and U.S. air-freight demand (in thousand ton-miles) are collected from the Bureau of Transportation Statistics (BTS) in the U.S. Department of Transportation (USDOT). U.S. per capita disposable income (in 2005 U.S. dollars) is used as a proxy for U.S. real income and is taken from the Bureau of Economic Analysis (BEA).[1] All variables are converted to natural logarithms.

Empirical Results

Although the ARDL is applicable irrespective of whether the variables are $I(0)$ or $I(1)$, the computed F-statistics are not valid in the presence of $I(2)$ variables. To ensure that none of the selected variables is $I(2)$ or beyond, we conduct unit root tests using the Dickey-Fuller generalized least squares (DF-GLS) test (Elliot et al. 1996). The results show that the null hypothesis for the level of $\ln AP_t$ can be rejected at the 5% level, suggesting that $\ln AP_t$ is stationary $I(0)$ process (Table 1). On the other hand, the null hypothesis for the levels of $\ln FP_t$ and $\ln Y_t$ cannot be rejected at the 5% level, while the null hypothesis for the first differences can be rejected at the 5% level, indicating that $\ln FP_t$ and $\ln Y_t$ are non-stationary

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[1] According to the literature (e.g., Liew and Liew 1979, Phu 1991), it seems more appropriate to include disposable income, instead of gross domestic product (GDP), in the demand for air service. This is because demand for air service is derived from traveler's budget for air transport, which is mainly determined by personal disposable income. In fact, we also use GDP as an alternative to disposable income to estimate equations (1) and (2) and find that the estimated coefficients are consistently insignificant. In contrast, our models that use disposable income show that the estimated coefficient is highly significant (Tables 3 and 4). Hence, disposable income should be more relevant in explaining air service demand.

$I(1)$ processes. Hence, we conclude that none of the variables is $I(2)$ and the ARDL modeling can be pursued on equations (1) and (2).[2]

Table 1. Results of DF-GLS unit root test

Variable	Level	First difference	Lag	Decision
$\ln AP_t$	-4.87**		1	I(0)
$\ln FP_t$	-0.89	-3.88**	4	I(1)
$\ln Y_t$	-0.46	-6.47**	3	I(1)

Note: ** denotes rejection of the null hypothesis of a unit root at the 5% level. The 5% critical value for the DF-GLS tests is -2.95. The lag order for the DF-GLS is chosen by the MAIC criterion.

The ARDL modeling begins with determination of the lag structure (p) in equations (1) and (2).[3] For this, we use the Schwarz Information Criterion (SBC) and Lagrange multiplier (LM) statistics for testing the null hypothesis of no serial correlation against lag length 1. The results indicate that $p=7$ and $p=10$ are the optimal lag lengths for U.S. air-passenger and air-freight services, respectively (Table 2). With the selected lag lengths, we then test the existence of long-run relationship (cointegration) among the variables in each model. As mentioned earlier, this amounts to conduct the F -test to determine the joint significance of lagged-level variables in equations (1) and (2); for this, the null hypothesis of non-existence of the long-run relationship is equivalent to $a_1 = a_2 = 0$ in equation (1) and $b_1 = b_2 = 0$ in equation (2). It is important to note that, since the results of the F -test is quite sensitive to changes in lag structure imposed on first differenced variables, we also use a negative and significant error-correction term (ec_{t-1}) as another criterion to determine the existence of the long-run relationship among the variables. The results of the F -test show that the calculated F -statistic for air-passenger demand lies above the upper critical value of 6.31 at the 10% level, while the test statistics for air-freight demand is found to fall below the lower level of 5.47 (Table 2). The coefficients of the error-correction terms in both models, however, are found to be negative and statistically significant at the 5% level (Table 2). We thus decided to proceed with assessing the short- and long-run coefficient estimates for the both models for which there seems to exist evidence of a cointegrating relationship.

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[2] The DF-GLS test statistics are estimated from a model that includes a constant and a trend variable. The MAIC criterion is used to determine lag lengths for the unit root tests.
[3] It is worth mentioning that, since the specifications in equations (1) and (2) are based on the assumption that the error terms are serially uncorrelated, it is crucial to balance between selecting a lag length (p) sufficiently large to mitigate the residual serial correlation problems and one sufficiently small to avoid being over parameterized, particularly in view of the limited time-series data available (Pesaran et al. 2001, p. 308).

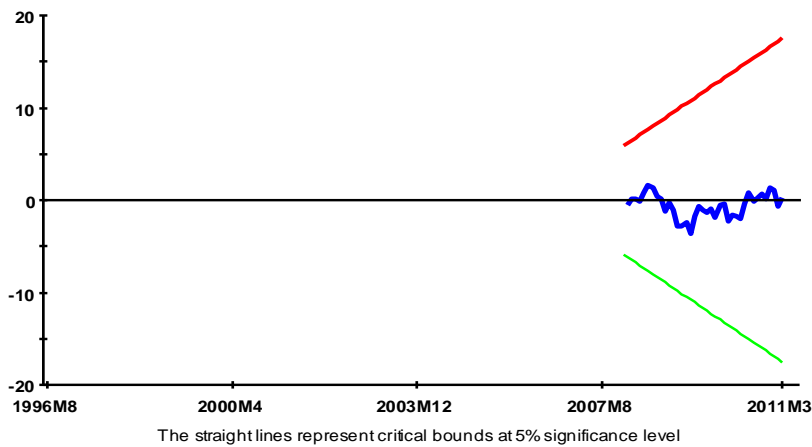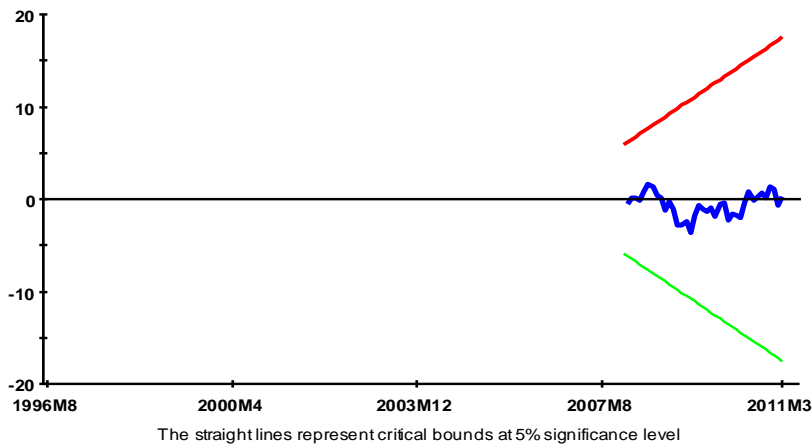**Table 2. Results of cointegration test among selected variables**

	Case I: $F(\ln AP_t \vert \ln Y_t)$	Case II: $F(\ln AF_t \vert \ln Y_t)$
Lag order	7	10
$\chi^2(2)$	3.78 [0.15]	4.06 [0.13]
F -statistic	23.12	1.89
ec_{t-1}	-0.85 (-7.02)**	-0.08 (-1.77)*

Note: $\chi^2(2)$ is Lagrange Multiplier (LM) statistic for testing the hypothesis of no serial correlation. *F*-statistic is the test statistics for cointegration. *F*-statistic for the 10% critical value bound is (5.47, 6.31). ** and * denote significance at the 5% and 10% levels, respectively. Brackets are *p*-values. Parentheses are t -statistics. ec_{t-1} is an error-correction term.

The results of the long-run models show that the coefficient of the U.S. real income is statistically significant at the 5% level in all two cases (Table 3). More specifically, the domestic real income has a positive long-run relationship with both the air-passenger and air-freight services, indicating that U.S. demand for air transport services tends to increase with economic growth. This finding further suggests that air-passenger and air-freight services can be treated as normal goods and services – an increase in income leads to an increase in air transport demand and vice versa. Notice that the air-freight service seems to be more responsive to income changes than air-passenger service in the long-run. Additionally, the dummy variable for the 9/11 terrorist attacks is found be significantly negative, indicating that the 9/11 terrorist attacks have depressed air-passenger service by approximately 17%. This finding substantiates the results of Ito and Lee (2005) and Blunk et al. (2006). For example, Ito and Lee (2005) find that the 9/11 terrorist attacks lead to an initial demand shock by over 30% and an ongoing downward shift in the airline demand by 7.4%. However, this finding contrasts with Lai and Lu (2005) in that the 9/11 terrorist attacks only have short-run impacts on U.S. air traffic. The dummy for the SARS epidemic is also found to have a negative effect on U.S. air-passenger demand (-6%). For the air-freight service, on the other hand, all the dummies are not statistically significant even at the 10% level, implying that the market shocks have little impact on U.S. air-freight markets.

The error-correction model (ECM) is estimated by the ARDL approach to capture the short-run dynamics among the selected variables (Table 4). The results show that the U.S. real income is statistically significant at the 5% level and has a positive relationship with U.S. air-passenger demand. This indicates that, as shown in the long-run analysis, air-passenger demand tends to increase with income in the short-run and thus can be treated as normal services. Additionally, the 9/11 terrorist attacks are found to significantly depress U.S. air-passenger service (-14%) in the short-run, whereas the other market shocks are found to have little impact. For the air-freight service, the real income is found to be statistically insignificant even at the 10% level, indicating that the real income is not an important determinant of the air-freight service in the short-run. One possible explanation for this finding is that the capacity of current air cargo infrastructure and service is limited and shippers may not quickly increase air freight volumes as economy grows. Another possible explanation is that the commodities shipped by air have high values and are very time-sensitive, which may limit shippers' choice of alternative transportation modes and reduce a substitution effect of air freight service when economy is in recession. In addition, as seen in the long-run analysis, all the market shocks are found to have little effect on U.S. air-freight volume in the short-run.

Finally, in order to ensure that estimated coefficients are stable over time, we apply the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests to the residuals of error-correction models in equations (1) and (2) (Figures 1 and 2). The result show that, with cases I and II, the estimated coefficients are generally stable over the sample period; hence, the ARDL models presented above are well defined and provide sound findings.

The straight lines represent critical bounds at 5% significance level

The straight lines represent critical bounds at 5% significance level

Figure 1. Plots of CUSUM and CUSUMSQ for demand for U.S. air passenger

Concluding Remarks

Economic growth in the U.S. has a significant effect on air service expansion. In this short paper, we have modeled the short- and long-run effects of economic growth on air passenger and freight services in the U.S., controlling for market shocks such as the 9/11 terrorist attacks, the Iraq war, the SARS epidemic, and the 2008 financial crisis. An autoregressive distributed lag (ARDL) approach is used to estimate the coefficients of the dynamic model.

The results of cointegrated analysis indicate the presence of a long-run relationship among the variables for both air passenger and freight services. This finding suggests that, when examining air transport demand, researchers need to incorporate the cointegration relationships; otherwise, the economic model could give rise to biased estimation.

We also find that, in the long-run, economic growth plays a crucial role in the expansion of both air passenger and freight services. This finding implies that policymakers and airline managers should be aware of appropriate measures (i.e., disposable income) of the likely effects of changes in economic activity on air transport demand and make decisions about long-term strategic planning, marketing, and business planning regarding air-passenger and freight service expansion and airport upgrade. In the short-run, on the other hand, only air passenger service is found to be sensitive to economic growth. Finally, it is found that, among the market shocks, only the 9/11 terrorist attacks and the SARS epidemic have significantly negative effects on air passenger service both in the short- and long-run, and in the long-run, respectively. However, the market shocks are found to have little impact on air freight service.

Together, our results provide the different responsiveness between U.S. air travel and freight services to the income changes, as well as the market shocks and explain why dynamic approach is needed for understanding U.S. airline industry and designing effective policy and management options.

Table 3. Results of estimated long-run coefficients

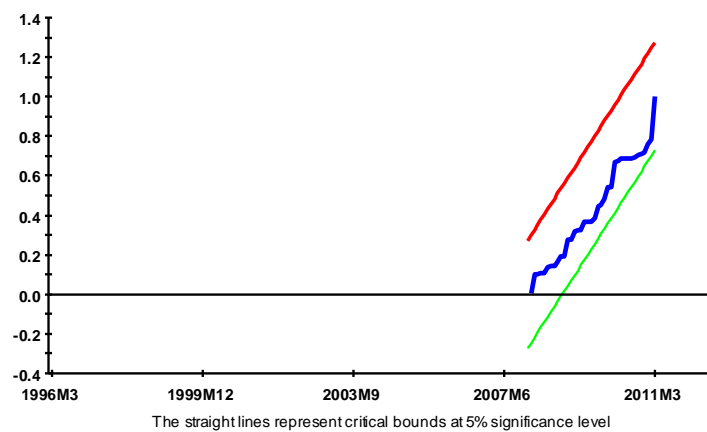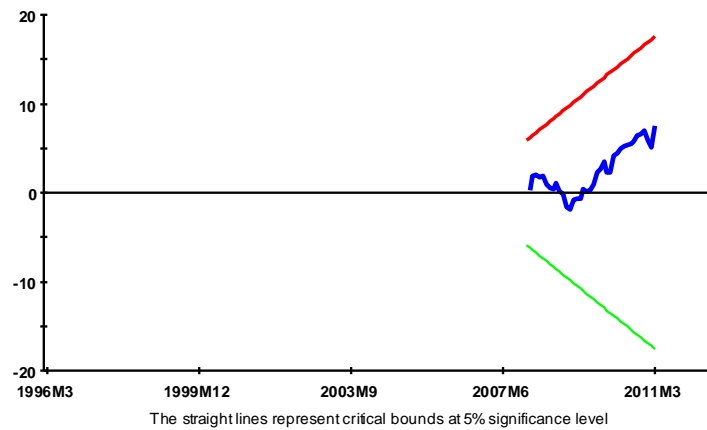| Variable	Case I	Case II
$\ln Y_t$	1.37 (15.47)**	7.08 (4.23)**
D_{911}	-0.17 (-6.37)**	-0.31 (-0.67)
$D_{recession}$	-0.01 (-0.46)	-0.41 (-1.21)
$D_{Iraqwar}$	-0.09 (-1.57)	0.41 (0.40)
D_{SARS}	-0.06 (-1.71)*	0.19 (0.30)
Constant	3.81 (4.19)**	-58.56 (-3.40)**

Note: ** denote significance at the 5% level. Parentheses are t-statistics.

Table 4. Results of estimated short-run coefficients

Variable	Case I	Case II
$\Delta(\ln AP_{t-1})$	0.31 (3.66)**	
$\Delta(\ln AP_{t-2})$	0.30 (3.81)**	
$\Delta(\ln AP_{t-3})$	0.33 (4.34)**	
$\Delta(\ln AP_{t-4})$	0.29 (3.86)**	
$\Delta(\ln AP_{t-5})$	0.34 (4.86)**	
$\Delta(\ln AP_{t-6})$	-0.38 (-5.56)**	
$\Delta(\ln AF_{t-1})$		-0.17 (-2.04)**
$\Delta(\ln AF_{t-2})$		-0.28 (-3.58)**
$\Delta(\ln AF_{t-3})$		-0.18 (-2.26)**
$\Delta(\ln Y_t)$	1.16 (6.51)**	0.53 (1.59)
D_{911}	-0.14 (-5.30)**	-0.02 (-0.63)
$D_{recession}$	-0.01 (-0.46)	-0.03 (-1.33)
$D_{Iraqwar}$	-0.07 (-1.58)	0.03 (0.40)
D_{SARS}	-0.05 (-1.61)	0.01 (0.30)

Note: ** and * denote significance at the 5% and 10% levels, respectively. Parentheses are t-statistics.

The straight lines represent critical bounds at 5% significance level

The straight lines represent critical bounds at 5% significance level

Figure 2. Plots of CUSUM and CUSUMSQ for demand for freight services

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