Low Cost Carriers and Airports Performance: Empirical Evidence from a panel of UK Airports.

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Abstract

During the last decade, the proliferation of Low Cost Carriers and the related huge increase in traffic has been the most visible effect of the deregulation of the airline market in Europe. Little attention has been paid to how airports were affected by the changes in the new institutional environment. In this study we model the total factor productivity (TFP) for a panel of the UK largest airports over the 2002-2005 period and investigate whether the presence of LCCs had some impact on airports' TFP. Empirical results are consistent with the hypothesis that conspicuous entry of LCCs on European markets has impacted positively on the vertical chain by facilitating airports' productivity improvements. This result is robust to reverse causality issues associated with the possibility that most efficient airports are those that are more likely to attract LCCs. Different possible arguments may explain our results: traffic increases brought about by LCCs for a given installed capacity might have generated higher TFP; more efficient organizational models might have been adopted to meet LCCs operational requirements (short turnaround times); cost reductions might have been realized in order to lower charges and attract LCCs; competition from a larger number of airports induced by LCCs' wider catchment areas (with respect to full service airlines) might have exerted further pressure toward TFP improvements.

Keywords: Total Factor Productivity, Airports, LCCs.

1 Introduction

In the United Kingdom (UK), the intensive process of liberalization of the airport industry, which started in 1986, brought about significant changes in the regulatory setting in which airports operate, in their ownership and governance structure and in the

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business models they implement (Parker, 1999). A decade later, a second liberalization at the European (EU) level tackled the other component of the air travel industry, by allowing European carriers to operate domestic flights in EU member countries other than their home market. In particular, this second liberalization eliminated entry barriers and induced the proliferation of low cost carriers (LCCs), thus favouring a considerable growth in the air traffic volume. These changes are likely to have induced airport strategies aimed at dealing with the new operating conditions brought about by the deregulated airline sector and, in particular, by the LCCs entry.

Several studies have analyzed airports efficiency with different approaches (Data Envelopment Analysis, Stochastic Frontier Analysis, Total Factor Productivity Analysis), focusing on different performance measures and on different efficiency drivers (see, among others, the surveys in Barros and Dieke (2008) and Fung et al.(2008)).[1] However, none has investigated the role on LCCs entry and just a few have analyzed if competition from other airports has a significant impact on productivity.[2] In this study, we develop an econometric model to study the extent by which the presence of LCCs has positively affected airports productivity.

The impact of the presence of LCCs on airports' performance may be related to two, possibly mutually reinforcing, mechanisms: first, the intensification of traffic volumes may have direct positive effects on airports' revenues from commercial, non-aeronautical activities; second, the new competitive environment faced by airports may be associated with a strong pressure to reduce airline charges. While this may negatively affect airports' financial performance, it may also have led to the restructuring and the streamlining of airports' activities, so that they could be more closely aligned with the particular needs of LCCs (Warnock-Smith and Potter, 2005): by doing so, airports may have gained from the realization of cost reductions and productivity improvements.

In this study we analyze the productivity of a sample of the 24 largest UK airports observed over the period 2002-2005. In particular, we adopt a two step estimation strategy where in the first step we conduct robust estimates of Total Factor Productivity (TFP) with different methodologies and in the second one we estimate an empirical model where productivity is considered (among other factors) as a function of the share of LCCs' passengers on total airports passengers traffic. This variable is meant to capture the strength of the pressure toward cost reductions and better organization experienced by each airport when faced with the presence of LCCs.[3] In particular we deal with the possibility that more productive airports are also those who mostly

[1] Among others we recall the study by Oum, Yan and Yu (2008) who found, for a sample of international airports, that majority private and fully publicly owned airports are the most cost-efficient; Oum et al. (2004) on a a sample of international airports have tested if different regulatory settings are associated with airports efficiency.

[2] See Yuen Chi-Lock and Zhang (2008) and Zhang et al. (2001) on Chinese airports and Malighetti et a.l. (2008) for a panel of italian airports.

[3] The first scheduled low-cost airline in Europe, Ryanair, started on the Dublin–London route in 1986. In August 1987, the first year of deregulation on the Dublin–London route, passenger traffic were 92% greater than in August 1985.

attract LCCs, thus generating possible bias in the estimate of the effect of the LCCs presence on productivity associated to reverse causality issues. Other airports specific characteristics, like the ownership structure, the composition of the traffic and the weight of passenger traffic, are included in the model; moreover, we also control for possible effects of localization by including multiplicative effects of time trends with dummy variables related to six different geographic markets. We also note that these market trend variables might also proxy for the (time varying) levels of competition faced by airports in their local geographic market and help to better identify the link between the presence of LCCs and airports' TFP. This kind of analysis has never been conducted before. Our findings support the hypothesis of a positive relationship between the intensity of LCCs presence in an airport and the latter's TFP.

The remainder of the paper is organized as follows. The next Section illustrates possible inter-related effects of the two liberalization processes. In Section 3 we present the data, while Section 4 describes the methodology adpted to estimate TFP. Main empirical results are discussed in Section 5 and Section 6 concludes.

2 Institutional setting

As far as its institutional setting is concerned, the present structure of the UK airport industry has been defined by the 1986 Airports Act which realized the privatization process announced in the 1985 White Paper on airports policy. At that time nearly all airports were owned by the public sector, either by the British Airport Authority (BAA) or by local governments.[4] In 1987 all the share capital of BAA were transferred to the private sector by flotation and BAA became BAA plc. Between 1993 and 1999 many (but not all) local government owned airport assets were also sold; moreover, ownership by unquoted private companies (BAA plc was the exception) has not prevented several of the airports changing hands since they were first transferred to the private sector, some several times (see table 2). The UK airport industry is thus a mixed private-public sector industry but dominated by the private ownership of assets with a strong presence of foreign investors.

At the time of privatization of BAA in 1987 it was assumed that major airports had significant market power, which called for the need of economic regulation. Airports designated to be regulated after the 1986 Airports Act were Manchester, Heathrow, Gatwick and Stansted. The sector specific regulator is the Civil Aviation Authority (CAA) and price-cap regulation was applied to airports charges with regulatory reviews scheduled every five years and caps set in order to allow for a rate of return consistent with the cost of capital.

By allowing full cabotage rights within all EU member states to all EU carriers in

[4]BAA had the largest share of the market as it owned seven airports, four in Scotland and three in the London region (Heathrow, Gatwick and Stansted), while the other largest local authority airport was Manchester.

1997, the European liberalization of the Civil Aviation market brought to the fore two new main players: Low-Cost Carriers (LCCs) and smaller regional airports (Warnock-Smith and Potter, 2005). The latter played a central role in facilitating the entry of the former, since traditional carriers, in the aftermath of deregulation, exercised "grandfather" rights, i.e., they maintained the slots in the main airports they operated prior to deregulation. By considering the UK airports' deregulation which took place a decade earlier, it might not be coincidental that LCCs (e.g., Ryanair and EasyJet) began their growth by establishing their bases in the UK: faced with limited access in main airports, LCCs strategically targeted less congested, secondary airports for their entry into the market, and subsequently designed their network expansion around them, given that such airports are endowed with excellent (and most often under-exploited) infrastructures, are conveniently positioned in largely populated areas and enjoy easy accessibility via a variety of transportation modes.[5]

A central argument in this paper is how the LCCs' business model may impact the operation of their airports. Typical aspects of such a model, which are shared by most LCCs, are centred on stripping out and avoiding all the complexity costs associated with traditional full service carriers (FSCs). Most notably, LCCs (i) use a simple pricing structure with one passenger class and fares only covering basic transportation (with optional paid-for in-flight food and drink); (ii) rely on direct selling through Internet bookings with electronic tickets and no seat reservations; (iii) operate simplified routes to often cheaper, less congested airports (with point-to-point rather than hub-and-spoke networks); (iv) employ intensive aircraft usage (typically with 25-minute turnaround times); (v) have employees working in multiple roles (e.g. flight attendants cleaning the aircrafts and acting as gate agents); and (vi) utilize highly standardized fleets with the same aircraft type.

The new environment faced by airports in the decade following the airline deregulation and the entry of LCCs, may have impacted on airports's performance in a number of ways.

First, the low fares charged by LCCs expanded the demand of airline services so as to include passengers that would not have traveled otherwise, thus boosting commercial revenues; in fact, by increasing passengers traffic, LCCs generate larger non-aeronautical revenue sources for airports, such as catering and shopping for services normally provided as in-flight services by full fare airlines, higher car rentals (especially for small airports) and higher commercial revenues. Furthermore an increase in traffic for a given capacity might imply a productivity improvement, as long as the composition of the traffic does not cause higher production costs.

Moreover, airlines deregulation and LCCs proliferation generated a new highly competitive operating environment that significantly reduced airports' market power. Such market power does not seem to derive from natural monopoly characteristics of technol-

[5] The key role of these airports is clearly illustrated by the fact that they were used for the creation of new routes by Ryanair and EasyJet, after their respective take-overs of Buzz and GoFly (Dobson and Piga, 2011).

ogy, but is most likely to be associated with land scarcity, locational and competition issues.[6] LCCs' countervailing power stems from the characteristics of their business-model which allows them to be more adaptable and to have substantial bargaining power in negotiating fees with airports. For instance, LCCs usually operate a point-to point network and do not offer connecting services, so that it is less costly for them to switch airports whenever it is the case. Furthermore, LCCs' wider catchment areas (with respect to FSAs) likely increased competition from nearby, and possibly more distant, airports by augmenting catchments overlaps.[7]

Following Warnock-Smith and Potter (2005), we argue that this new competitive scenario may also have contributed to the introduction of airports' managerial practices that have positively impacted on their profitability. For instance, LCCs short turnaround times might have required more efficient operational processes; the willingness to guarantee low charges to LCCs might have led to further cost reductions and efficiency improvements: secondary airports (as well as airports with public service obligation -PSO- and regional development goals) were forced to design their activities and production processes in order to maximize the chances of securing the profits generated by the new institutional arrangement.

Despite the reduction in market power vis-a-vis both airlines and competing airports, the potential benefit from LCCs' presence, as well as the observed efforts by airports in establishing a relationship with LCCs, suggest that the existence of complementarities between the demand for aviation services and the demand for concession services is another factor which may compensate airports for their loss of market power.[8] Our econometric approach therefore focuses on the net impact that the presence of LCCs exerted on airports' productivity.

As far as previous evidence on performance determinants for the UK airport industry is concerned, we mention, among others, Parker (1999), Barros (2008) and, in particular, Barros and Weber (2009) who have analyzed technical efficiency and total factor productivity for a sample of 27 UK airports observed over the period 2000-2005 and have found, among other results, that the majority of UK airports did not improve efficiency over the sample period. In turn, Bottasso and Conti (2011) provided a detailed analysis of the cost structure of the UK airport industry for the period 1994-2005

[6]Bottasso and Conti (2011) have shown that average costs curve is U shaped for the UK airport industry.

[7]Bel and Fageda (2010) using data for 100 large airports in Europe find, among other things, that competition from other transport modes and nearby airports imposes some discipline on the pricing behavior of airports.

[8]It is worth recalling that airlines deregulation has also caused a significant change and shift in risk so that airports now have incentives to negotiate long term contracts with carriers in order to share the risk of traffic losses. An interesting case study of how the Spanish airport of Girona managed its relationship with Ryanair can be found in Bel (2009). While the story of Girona may be echoed by similar experiences in other Continental European airports whose majority ownership has remained in the hands of either the State or regional governments, the UK airport deregulation has likely lessened the incentive for UK airports to pursue other objectives than strict profit maximization.

and found a positive rate of technical change over the sample period.

3 Data

The dataset used in this study consists of a balanced panel of the major 24 UK airports observed over the period 2002-2005. The main source of data is the statistical series "The UK Airport Industry" published each year by the Centre for the Study of Regulated Industries at the University of Bath. Additional information was obtained from airports accounts, from UK National Statistics and from the UK Civil Aviation Authority (CAA).

The summary statistics reported in Table 1 suggest that in the UK airport industry there is high variability in terms of size. In particular, the size distribution of airports is highly skewed to the right: for example, if we consider the airport total number of passengers (*pax)*, about 78% of the observations have a lower value than the mean, and similarly in the case of the work load units (*wlu)*, defined as one passenger or 100 kg of cargo and mail. The skewness of the size distribution is driven by the presence of two very large airports, notably Gatwick and, in particular, Heathrow.

Similar conclusions can be drawn by observing data on deflated total revenues (*tot rev*), computed as the sum of charges and commercial revenues and on our output measure (*y),* computed as the weighted average of working load units (*wlu*) and other operating revenues, each weighted by its share in total revenues.

The revenues shares deriving from commercial activity (*share other rev*) and from charges (*share charge rev*) are approximately equal (around 50%) and stable over time. The standard deviation suggests a certain degree of variability across airports, with Blackpool airport displaying the largest share of commercial revenues (75% on average).

Concerning this issue, many studies ignore the non-aeronautical service outputs (commercial services including concessions, rentals, car parking, etc.) airports produce. Since airports inputs are not usually separable between the aeronautical and the non-aeronautical service activities, any productivity measure which excludes the non-aeronautical services outputs would bias empirical results very seriously against the airports generating a larger portion of their revenues from commercial services.

Input variables used in order to estimate airports TFP are labor (l), materials (m) and capital (k). Labor is represented by the number of employees; materials are proxied by the cost of non labor inputs (operating expenditures other than labor costs) deflated with a specific price index which has been computed as the weighted average of *i*) the Construction Output Price Index -COPI- (as a proxy for the price of materials); *ii*) a price index of water, gas and electricity services and *iii*) the RPI (as a proxy for the price of other services paid by airports).[9] The perpetual inventory method was used to reconstruct a series of the capital stock. In particular, for many airports we have

[9] The weights have been proxied by the cost shares of materials, utility bills and residual services in non-wage costs as reported in BAA airports statutory accounts, respectively.

exploited the capital stock revaluations that have occurred over our sample period and we have considered the revaluation year as the baseline.[10]

Overall, the time pattern of main variables confirms the positive trend of aviation markets which took place over the first decade that followed the airline market deregulation: total revenues increased by approximately 15% between 2002 and 2005 and the number of passengers increased by about 20%.

Other variables used in the empirical analysis are the percentage of international passengers (*pip)* and the percentage of passenger traffic (*ppt)*, obtained as the number of passengers divided by *wlu*. These variables reflect the composition of airports traffic and depend largely on the geographic location of the airport. Both variables may influence airports performance since they are associated with different amounts of revenues and costs.

As far as the ownership definition is concerned, we have defined an airport as "public" (*pub*) whenever the majority ownership belongs directly or indirectly to one or more municipalities; in turn, an airport has been defined as "mixed" (*mix*) whenever private investors retain the majority control but local councils hold a substantial minority stake (i.e. bigger than 20-30%) or when the airport is under public ownership but the management is fully delegated to private investors (e.g. Luton after 1998); finally, an airport that does not belong to either groups is defined as "private" (*priv*). As of 2002, 9 airports in our sample were publicly owned, against 12 under private ownership and three which are defined as *mix*; in turn, in 2005, 13 airports were privately owned, against 6 and 5 under public and mixed ownership, respectively. Table 2 reports, for each airport, its ownership status and its changes over the sample period whenever they occurred.

Turning to variables which reflect the presence of LCC on airports, the main data source is the Civil Aviation Authority (CAA) which provided secondary data on the traffic for all routes and airlines flying from all the main UK airports in the sample to the following European countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Czech Republic, Norway, Sweden, Switzerland as well as the UK, whose domestic routes were also considered.

The dataset includes monthly flights information from June 2002 up to, and including, June 2005, for a total of 37 months. For each combination of company, route and departure period (i.e., month/year), the CAA provided the number of monthly seats, the number of monthly passengers and the monthly load factors. These were broken down at the flight identification code level, that is, for each flight operated by all the airlines in a given month and route, so that the total number of monthly flights could also be obtained. Then, for each airline, traffic statistics were aggregated at both the route and at the airport level. This allowed the possibility to create proxies for the presence of each airline at the airport level and the market level, where a market can

[10]We have assumed a constant depreciation rate of 4.5%. The resulting capital stock series was deflated with the COPI index.

contain a wider set of airports located in a given geographical area. In particular, we were interested in measuring the presence of the three largest LCCs operating in British airports: Ryanair, EasyJet and FlyBe. Therefore, we calculated the sum of the total number of flights and passengers of these three carriers, and then obtained their share on the total number of passengers or flights for each airport or market.

To this purpose we divided the airports in our sample into six different geographic markets, partly on the basis of considerations developed by both the Office of Fair Trade and the Competition Commission in the recent BAA case, and partly on our assessment based on distances between airports (two hours driving time). The markets identified by the Competition Commission and the OFT studies were the London area and Scotland; moreover we have identified four additional markets so that we have six markets in total, namely, Mkt 1: Heathrow, Gatwick, Stansted, London City, Luton, and Southampton, Norwich; Mkt 2: Manchester, Humberside, Nottingham, Birmingham, Blackpool, Leeds and Liverpool; Mkt 3: Glasgow, Edinburgh and Aberdeen; Mkt4: Bournemouth, Cardiff, Bristol and Exeter; Mkt 5: Newcastle and Durham; Mkt 6: Belfast.

Table 3 indicates that the share of passengers of the 3 largest LCCs in each airport tends to be very similar in markets 1, 2 and 5, where about 40-50% of passengers on both UK domestic and inter-European routes fly with one of the 3 largest LCCs. A large presence is recorded for market 4, while in market 6 the preponderance of LCCs' presence is quite striking, since the share of LCCs passengers in an airport reaches values up to 80%. However, the relevant variation across airports in a market, as revealed by the measures of standard deviation in Table 3, indicate that the presence of LCCs is quite heterogeneous across airports in a given market, and that therefore it is an important factor that needs to be controlled for in the empirical analysis. Finally LCCs' presence has increased in most markets over the sample period; in particular for market 4 their passengers share has grown by 50%.

4 Total Factor Productivity estimation

In order to measure airports' unobserved Total Factor Productivity (TFP) we follow the standard approach of estimating it as the residual of a production function: within this framework TFP measures output variations which are not explained by inputs variations.

We assume that airports' technology can be described by a Cobb Douglas production function. This simple specification allows us to easily understand if relevant estimated coefficients and return to scale measures assume reasonable values which are coherent with economic theory.

The Cobb Douglas production function can be defined as:

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \tag{1}$$

where Y_{it} is a measure of output, K_{it}, L_{it}, M_{it} are inputs capital, labour and materials and A_{it} is the unobservable TFP component which affects all marginal factors productivity simultaneously; moreover if $\beta_k + \beta_l + \beta_m = 1$ the technology is chacterized by constant returns to scale.

Taking natural logs of equation (1) allows us to obtain a linear estimating model like:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + u_{it} \tag{2}$$

The term u_i is the log of the firm specific TFP and is usually split into two components:

$$u_{it} = a_{it} + e_{it} \tag{3}$$

where a_{it} represents firm level productivity observable by the firm but unknown to the researcher, while e_{it} is an i.i.d. component accounting for measurement errors and unexpected shocks.

After estimating equation (2) the TFP levels can be recovered as:

$$\exp(\widehat{a}_{it}) = y_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_m m_{it} \tag{4}$$

Evaluating TFP as a residual of a production function estimated on firm level data implies some econometrics problems which may conduct to biased estimates if not accounted for: possible problems are linked to the endogeneity of inputs choice, to selectivity and attrition and to omitted prices bias.[11]

We focus on the simultaneity issue stemming from the fact that firms observe TFP realisations and use them in order to make their inputs profit maximizing choice: this introduces a correlation between the error term u_{it} and the regressors in equation (2) that makes OLS estimates biased. It has been shown (Levinsohn and Petrin (2003)) that the estimation bias in inputs elasticities have opposite directions, depending on wether they are variable or fixed factors, so that it is not easy to define the expected impact on TFP estimates.

The most common estimation approaches adopted in order to deal with endogenity issue are fixed effects and instrumental variables techniques and, more recently, the semi-parametric approach by Olley and Pakes (1996) and Levinsohn and Petrin (2003).[12]

In our empirical application we first estimate equation (2) by OLS so as to obtain benchmark values for TFP; successively, in order to get consistency of the production

[11] Van Biesebroeck (2007) and Van Beveren (2010) provide excellent rview on TFP estimation.

[12] The fixed effect estimation technique is based on the assumption that the firm specific productivity component (a_i) is time invariant so that equation (2) can be estimated after an approriate transformation of the data (first difference or within transformation) or by the inclusion of a complete set of firm specific dummy variables. However, the fixed effect estimator neglects cross sectional variation and assumes that inputs are strictly exogenous.

function parameters estimates, we apply both an instrumental variable technique and a semiparametric approach.

Instrumental Variables (IV) techniques account for endogenity of regressors through the use of valid instruments: given the difficulty of finding valid external instruments (correlated with endogenous regressors and uncorrelated with the error term), we estimate equation (2) with the Generalized Method of Moments (GMM), as suggested by Blundell and Bond (1999). Within this approach the productivity term (a_i) is modeled as a firm fixed effect with an autoregressive component. After first differencing the production function in order to get rid of the fixed effects, lagged inputs can act as instruments for changes in inputs; however, when input variables are persistent over time, their lags are weakly correlated with their changes, so Blundell and Bond (1999) suggest to estimate a system where equation (2) enters both in levels and in first differences: lagged first difference of inputs are used as instruments in the level equation, while lagged inputs are used as instruments in the first difference equation (GMM-SYS method). This estimation technique improves estimates efficiency but requires data for a reasonable time span.

Consistent estimation of the input parameters of the production function can also be achieved by applying the semi-parametric approach suggested by Levinsohn and Petrin (2003), which builds on the estimator proposed by Olley and Pakes (1996). These methods tackle the simultaneity issue by recovering information on the unobservable productivity term from other observable firm's choices: in particuar the Olley and Pakes (1996) approach uses firm's investment decisions, while Levinsohn and Petrin (2003) rely on intermediate inputs as a proxy variable for productivity, which in turn is assumed to follow a first order Markov process:

$$a_{it} = E\left[a_{it} \mid \Omega_{it}\right] = E\left[a_{it} \mid a_{it-1}\right] + v_{it} \tag{5}$$

where Ω_{it} is the information set at time t and v_{it} represents unanticipated shocks on productivity.

Levinsohn and Petrin (2003) assume that firms choices on labour and intemediates are undertaken at time t, when productivity is observed by the firm, while capital is chosen at time (t-1); intermediates are assumed to be a monotonic function of capital and productivity:

$$m_{it} = m\left(a_{it}, k_{it}\right) \tag{6}$$

Substituting equation (6) in equation (2), we get:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \gamma m_{it} + a_{it} + e_{it} \tag{7}$$

If intermediates are an increasing function of a_{it}, equation (6) can be inverted in order to recover a proxy for productivity:

$$a_{it} = h\left(m_{it}, k_{it}\right) \tag{8}$$

After substitution in the production function, equation (2) becomes:

$$y_{it} = \beta_l l_{it} + \Phi_{it}\left(m_{it}, k_{it}\right) + e_{it} \tag{9}$$

where

$$\Phi_{it}\left(m_{it}, k_{it}\right) = \beta_k k_{it} + \gamma m_{it} + h\left(m_{it}, k_{it}\right) \tag{10}$$

Equation (9) can be fitted after approximating $\Phi_{it}\left(m_{it}, k_{it}\right)$ with an high-order polynomial so that it is possible to recover consistent estimates for the coefficient of the labour input; capital and intermediates coefficients are identified in a second step. By using first step estimates of β_l and equation (5) Levinsohn and Petrin (2003) derive the second step estimating "net output" equation as:

$$y_{it} - \widehat{\beta}_l l_{it} = \widehat{\Phi}_{it-1} + \beta_k\left(k_{it} - k_{it-1}\right) + v_{it} \tag{11}$$

where $v_{it} = e_{it} + u_{it}$ and $\widehat{\Phi}_{it-1} = y_{it-1} - \widehat{\beta}_l l_{it-1}$.

Given that intermediates are correlated with the error term u_{it}, estimating equation (11) with OLS would provide inconsistent parameter estimates, hence Levinshon and Petrin (2003) suggest to apply GMM in order to recover $\widehat{\beta}_k$ and $\widehat{\gamma}$ and derive TFP.[13]

In this study we evaluate three different measures of TFP obtained by estimating equation (2) with OLS (TFP_1), with the Levinshon and Petrin (2003) method (TFP_2) and with the GMM-Sys estimator (TFP_3).

Estimated TFP levels (available from the authors upon request) show consistent results across estimation methodologies, with rank correlation coefficients ranging between 0.62 and 0.74. Moreover, TFP values display a positive pattern over time with a slightly increase in dispersion.

The Cobb Douglas functional form that we have assumed finds increasing returns to scale that are constrained to take on the same value for all airports, independently from their size. However, if largest airports operate under constant or even decreasing returns to scale (Bottasso and Conti, 2011) and output grows over the sample period, we might be underestimating their TFP. As a robustness check we have also estimated a translog pruduction function, which provides a second order approximation to an unknown functional form and therefore does not constrain returns to scale to be constant along the size distribution. Results are however very similar to those presented in the paper and are available from the authors upon request.

[13] For technical details see Levinshon and Petrin (2003).

5 Empirical results

Different TFP measures obtained in the first step and labeled as TFP_1, TFP_2, TFP_3 in Table 4, are the dependent variables of the second step of our analysis, where we allow TFP to depend on the presence of LCCs in each airport and on different variables which account for airports' characteristics, including ownership structure and traffic composition.

On the basis of the definitions of public and private airports given in the data section, we include in the model two ownership dummies (*dpriv* and *dpub*), with airports with mixed ownership considered as the reference group. The standard argument suggested by the literature on the effects of privatization on firms performance is linked to possible heterogeneity in managers' objective function associated with different ownership forms; moreover, different governance structures generate different agency relationships among stakeholders which may also influence productivity. The inclusion of ownership dummies is also important since managers of airports characterized by various ownership structures may have different incentives in attracting low cost airlines and therefore failing to control for an airport ownership status might lead to an omitted variable bias problem.

Traffic composition is included as a possible variable affecting productivity, since different kinds of traffic have different implications on airports costs and revenues. Usually, high percentages of international passengers (*pip*) and lower percentages of air cargo (high *ppt*) are expected to increase production costs and lower total factor productivity, given that international traffic and passengers traffic require more services, space and resources, with respect to domestic traffic and cargo traffic.

The main variable of interest in this paper is the share of passengers of the 3 largest LCCs in each airport (labeled as $LCCs$ in Table 4) which proxys for changes in operating conditions faced by airports: we argue that LCCs presence in an airport might be associated with lower costs and higher productivity, since such airlines requires low charges and high efficiency in operating conditions at airports; moreover, their presence enlarges the potential for competing airports since they have wider catchment areas with respect to FSAs.

The estimated equation can be written as:

$$\begin{aligned} \ln TFP_{it} &= \alpha + \beta \ln TFP_{it-1} + \gamma LCCs_{it} + \delta dpriv_{it} + \zeta dpub_{it} + \\ &\quad + \eta pip_{it} + \theta ppt_{it} + \lambda_j(tmkt_j) + \mu_i + w_{it} \end{aligned} \tag{12}$$

where μ_i reflects a time invariant airport specific error term capturing non observable airport characteristics which may affect TFP, such as managerial ability or airport infrastructure; w_{it} is an error term, while the regressors have been defined above. In equation (12)we have also included the first lag of TFP in order to model possible persitence in TFP.[14]

In order to control for regional and/or market level heterogeneity we included a full set of interaction terms between market dummies and a time trend ($t*mkt_j$) that proxy for time varying unobserved heterogeneity in the geographic market j where the airports operate and account for shocks that may hit the markets where the airports are located, as well as for different developments in the economic and competitive environment they face; in particular, they should capture both the regional specific business cycles and the (changes in) intensity of competition in each particular market, or in other locational related variables (e.g. population density, transport infrastructure, income wealth of the local population, economic development and so forth). Indeed, a recent detailed analysis conducted by the CAA and by the UK Competition Commission (2008) revealed that there is significant potential for airport competition in both the London and the North West (Manchester) regions of the UK as a result of the presence of significant overlaps in catchment areas and such characteristics should be captured by our market trends.[15]

Turning to the empirical results, we have first estimated the model by OLS on pooled data. Table 4 reports OLS results for each of the three measures of TFP obtained in the first step.

OLS estimates provide a very high and significantly positive coefficient for lagged TFP and a positive correlation between LCCs passengers' share and TFP of about 0.2, thus suggesting that the presence of LCCs operating in an airport may lead the latter to improve its TFP; however, none of the other explanatory variables turn out to be significant. Nevertheless, a potential pitfall of these results is that OLS techniques do not take into account possible problems of endogeneity, which in our model might be generated by unobserved heterogeneity, feedback effects and measurement errors.

Given that some of our explanatory variables are potentially correlated with the unobservable, time-invariant airport level component represented by μ_i, we can remove this first source of endogeneity by appropriately transforming the model (i.e by first difference or within transformation). Another source of endogeneity is associated to the lagged dependent variable and to the share of passengers of the 3 largest LCCs in each airport. The presence of these regressors makes both the within group and the first difference estimators biased and inconsistent. In this case the standard solution is to get rid of the individual effects by first differencing the data and then using longer lags of $\ln TFP_{t-1}$ (e.g. $\ln TFP_{t-2}$) as instruments in a GMM fashion, along the lines proposed by Arellano and Bond (1991) or Arellano and Bover (1995); similarly, suitable instruments for $LCCs$ need to be employed. However, when the number of cross sections is small, as in our case where N=24, these estimators could be imprecise as

[14] We can note that main results do not hinge upon the presence of the lagged TFP term.

[15] Nevertheless the CC suggested that common ownership of three London airports by BAA was likely to adversely affect competition and in a successive report (2009) ruled BAA would have to divest itself of airports in either Gatwick or Stansted, and either Edinburgh or Glasgow. In December 2009 BAA sold Gatwick to Global Infrastructure Partnership.

their consistency properties hold for large cross sectional dimensions; furthermore, our panel is also short (T=5), and using longer lags as instruments might reduce available observations. For this reason we have followed a different strategy, namely presenting different estimation methodologies that separately tackle endogeneity concerns on $\ln TFP_{t-1}$ and on $LCCs$ and comparing the results as a robustness check.

As far as the share of LCCs passengers is concerned, if we assume the current period disturbances to be uncorrelated with past and current values of $LCCs$, but potentially correlated to its future values, we can first difference the model and then apply an IV method, using $LCCs_{it-1}$ as an instrument for $LCCs$. In fact, there might be reasons to believe that, even after controlling for time invariant unobserved airport heterogeneity and market specific time trends, a past shock to productivity might still be correlated with entry of low cost airlines as of time t: for example, poor past performance of an airport might have discouraged entry or expansion of LCCs in that airport. We followed the above estimating approach by estimating with 2SLS equation 1 after first differencing the model. The results (not shown) confirm a positive and significant correlation between TFP and the presence of LCCs.[16]

However, the above assumption of predeterminedness for $LCCs$ may in some cases be violated: in fact, if a current shock to TFP leads to successive entries of low cost airlines, the assumption of predetermination would fail and we would have to use longer lags as valid instruments (t-2), which is not advisable in such a short and small panel; furthermore, if low cost airlines forecast future TFP and decide to enter or to expand in a particular airport on the basis of these forecasts, the variable $LCCs$ would be fully endogenous and lagged values would no longer be valid instruments.

An alternative approach is therefore to search for "external instruments": the growth of value added in the NUTS1 region where the airport is located and the number of nights spent for business reasons in each airport's region are included as external instruments for $LCCs$.[17] The rationale for using value added growth in the region as an instrument is that low cost carriers might find more opportunities to enter or to expand their business in regions characterized by strong economic growth, while it seems unlikely that regional value added growth is correlated with an airport TFP, especially after controlling for airport fixed effects and market specific time trends. Moreover, using the number of nights spent for business reasons as an instrument for $LCCs$ rests on the assumptions that low cost carriers might find it relatively more profitable to serve airports that are located in regions where many people need to travel for business reasons and that, at the same time, the number of nights spent for business reasons in the region does not affects directly airports' TFP, but indirectly influence it

[16] Interestingly, the dummy related to public ownership of airports assumes positive values, thus implying that airports whose majority ownership belongs directly or indirectly to one or more municipalities are more efficient than those where private investors retain the majority control but local councils hold a substantial minority stake. This result is consistent with Oum, Yan and Yu (2008) findings on a sample of international airports.

[17] This information was taken from various waves of the Family Spending Survey.

by attracting more $LCCs$.

In order to tackle drawbacks stemming from the possibility that our chosen instruments are weakly correlated with $LCCs$,[18] we followed an empirical strategy based on some recent econometric works (Hahn and Hausmann (2005) among the others) which show that some IV estimators, such as the limited information maximum likelihood (LIML) and the Continously Updated GMM Estimator (CUE) proposed by Hansen et al. (1996), seem to be less subject to the weak instruments problems.[19]

Parameter estimates reported in Table 4 and labeled "CUE-FE" are based on the estimation of equation 1 (after the within transformation) with the CUE-GMM estimator and broadly confirm the results obtained with previous regressions: in particular, the effect of LCCs on TFP is found to be higher than in the OLS case (around 0.9) and statistically significant at the 5% level.[20]

Turning to the endogeneity issue stemming from the presence of the lagged depend variable in the empirical model, we tried to tackle it by applying the least square dummy variable (bias) corrected estimator (LSDVC) proposed by Kiviet (1995), which appears particularly suitable when the conditions underlying the use of the GMM-DIFF of Arellano and Bond are unlikely to be met (Judson and Owen (1999)). However, we should bear in mind that this estimator requires strict exogeneity of the other regressors so that it does not take into account possible biases arising from the presence of other endogenous explanatory variables.

Estimates obtained by applying the LSDVC estimator are shown in Table 4: the coefficients of lagged TFP are significantly positive and range between the higher values obtained with OLS and the lower values from the CUE-GMM FE estimates.[21] Moreover, LSDVC estimates confirm the positive impact of $LCCs$ on productivity with a similar magnitude to that obtained in the CUE-GMM FE case; in turn, we find a pos-

[18] In small samples, the presence of weak instruments could make IV estimators biased and standard errors invalid (Staiger and Stock, 1997).

[19] The CUE GMM estimator is a modification of the two-step efficient GMM estimator where the weighting matrix is not estimated in the first step but it is assumed to be a function of the regression parameters and estimated using non linear algorithms in a single step.

[20] First stage regressions show that both instruments are positively and significantly correlated with the share of LCCs in the airport. We have also tested for the existence of a weak instrument problem: one possible definition of the weak instrument problem (Stock et al, 2002) is that instruments are weak if the α-level Wald test based on IV statistics has an actual size that exceed a certain threshold, such as 10% or 15%. For example, in the TFP_1 model, the tabulated maximum critical values for an actual size of 15% (instead of the nominal 5%) is 5.33, which is lower than the Kleibergen-Paap rk statistics of 5.7. This suggests that the maximum size distortion in this application is no larger than 10%: we interpret this result as evidence that CUE-GMM estimates are not affected by serious weak instrument problems. Furthermore, the Hansen J statistics rejects at the 10% level the hypothesis that the instruments are correlated with the error term. Very similar results were obtained with the LIML estimator. All regressions were run using the XTIVREG2 routine in STATA.

[21] In dynamic panel models it is well known that the presence of unobserved individual heterogeneity will downwardly bias the coefficient of the lagged dependent variable. This is known as Hurwicz bias (after Leonid Hurwicz, who noted this effect for time series half a century ago) or Nickell bias (after Stephen Nickell who rediscovered and applied it to panels 20 years ago).

itive and statistically significant coefficient for the public ownership dummy in models TFP_1 and TFP_3.

To sum up, overall results suggest that the presence of LCCs has a positive impact on airports total factor productivity in all estimated models. Our preferred model is the one estimated with Fixed Effect CUE-GMM, as it accounts for endogeneity issues by relying on external instruments and provides estimates for the parameter of the lagged TFP quite similar to those obtained with LSDVC estimator (in the case of models TFP_2 and TFP_3). The average value for the coefficient of the $LCCs$ variable obtained with CUE-FE is about 0.85, which implies that a standard deviation increase in the share of passengers of LCCs in an airport would have a contemporaneous positive impact on TFP of about 27%; moreover, its long run impact, obtained by dividing the contemporaneous effect by 1 minus the average coefficient of lagged TFP, results to be about 30%.

Turning to vari ables related to traffic composition, they do not seem to affect airports TFP: it may be the case that production costs differentials associated with different traffic compositions are compensated by the large increase in passengers traffic which took place after the deregulation of the airlines market; however, further analysis should be conducted on this issue, possibly on a longer time span. Finally, there is partial evidence of higher productivity of public airports with respect to those characterized by mixed ownership.

6 Conclusions

The decade following the deregulation of the Civil Aviation market has been a period of great changes for the European airport industry. Airports had to adapt to new operating conditions brought about by the liberalization of the airline industry, which has favoured proliferation of LCCs and huge increases of traffic. The new environment is characterized by higher pressure on airports toward costs reduction and productivity improvements which are necessary to attract LCCs and to compete on enlarged relevant markets.

Changes in ownership and governance structure, different organizational models and new vertical relationships between airports and airlines are some of the adjustments observed in the European airport industry and, in particular, in the UK case.

In this study we analyze if estimated Total Factor Productivity for the 24 largest UK airports is affected, among other things, by the presence of LCCs, which has been proxied by the share of LCCs' passengers on total passengers traffic at each airport. The empirical analysis has been conducted with a two step approach, whereby TFP has been estimated with different econometric techniques in the first stage and, in the second step, a dynamic panel model of an airport TFP has been estimated by regressing first step fitted values of TFP on a set of explanatory variables which include ownership forms, airport specific characteristics and the share of LCCs on total passengers. In our econometric analysis we have controlled for airport unobserved heterogeneity, market level trends and reverse causality issues.

Empirical results are consistent with the hypothesis that LCCs entry on European markets has stimulated airports productivity improvements together with fare reductions for passengers.

Different possible arguments may explain our results: traffic increases brought about by LCCs for a given installed capacity might have generated higher TFP; more efficient organizational models might have been adopted for meeting LCCs operative standards (short turnaround times); cost reductions might have been realized in order to lower charges and attract LCCs; competition from a larger number of airports induced by LCCs' wider catchment areas (with respect to FSAs) might have exerted further pressure toward TFP improvements.

Possible policy implications of our findings are linked to regulatory issues and, in particular, add some elements to the debate on the opportunity of regulating the industry. Some authors argue that there is no need for regulation since possible abuse of airports market power is prevented by different factors, like the existence of complementarities between the demand for aviation services and the demand for concession services. More generally, market power might have been reduced by the increasing degree of competition between airports, which in turn is a direct consequence of the liberalization of European air transports and of the growing importance of Low Cost Carriers.

Our findings, coupled with the evidence of diseconomies of scale for high traffic levels which undermine the natural monopoly argument for economic regulation, reinforce the view against the need for regulation of the airport industry.

References

[1] Barros C. P. (2008) The Technical Efficiency of UK Airports. Journal of Air Transport Management; 14, 175-178.

[2] Barros C. P and. Dieke P. (2008) Measuring the economic efficiency of airports: A Simar–Wilson methodology analysis. Transportation Research Part E, 44:1039–1051

[3] Barros C. P. and Weber W.L. (2009) Productivity Growth and Biased Technical Change in UK Airports. Transportation Research Part E ; 45, 4, 64.

[4] Bel G. (2009). How to compete for a place in the world with a hand tied behind your back: The case of air transport services in Girona. Tourism Management, 30:522–529.

[5] Bel G. and Fageda X. Privatization, regulation and airport pricing: an empirical analysis for Europe. 2010, Journal of Regulatory Economics, 37:142–161.

[6] Bottasso A. and Conti M. (2011). The Cost Structure of the UK Airport Industry. Journal of Transport Economics and Policy, forthcoming.

[7] Competition Commission. BAA Market Investigation: Emerging Thinking. London 2008.

[8] Dobson, P. and C. Piga (2011). The Impact of Mergers on Fares Structure: Evidence from European Low-Cost Airlines, Economic Inquiry, forthcoming.

[9] Fung M., Wan K., Hui Y. and Law J. (2008) Productivity Changes in Chinese Airports 1995-2004. Transportation Research Part E, 44, 521-542.

[10] Hahn L., Hausman J. and Kuersteiner G. (2004). Estimation with Weak Instruments: Accuracy of Higher-Order Bias and MSE Aprroximation. Econometric Journal, 7: 272-306.

[11] Hansen, L., Heaton, J., and Yaron, A. (1996). Finite Sample Properties of Some Alternative GMM Estimators. Journal of Business and Economic Statistics, 14:262-280.

[12] Kiviet J.F. (1995). On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models. Journal of Econometrics, 68: 53–78.

[13] Judson R.A. and Owen A.L. (1999) Estimating Dynamic Panel Data Models: A Guide for Macroeconomists. Economics Letters, 65:9-15.

[14] Littlechild S. (2003). Reflections on Incentive Regulation. Review of Network Economics, 4:289-315.

[15] Malighetti P., Martini G., Paleari S. and Redondi R. (2008). The efficiency of European airports: Do the importance in the EU network and the intensity of competition matter? Working Paper University of Bergamo, 4.

[16] Office of Fair Trade (2009) UK airports. Report on the market Study and Proposed Decision to Make a Market Investigation Reference, London .

[17] Oum, T.H., Zhang, A., Zhang, Y. (2004). Alternative forms of economic regulation and their efficiency implications for airports. Journal of Transport Economics and Policy, 38:217–246.

[18] Oum T.H. and Fu X. (2008) Impacts of Airports on Airline Competition: Focus on Airport Performance and Airport-Airline Vertical Relations. OECD Joint Transport Research Centre, Discussion Paper, 17.

[19] Oum T.H., Yan J. and Yu C. (2008). Ownership Form Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports. Journal of Urban Economics, 64:422-435.

[20] Parker D. (1999). The Performance of BAA Before and After Privatization. Journal of Transport Economics and Policy, 33, 3:133-146.

[21] Piga C. and Bachis.E. (2007). Pricing Strategies by European Traditional and Low-Cost Airlines: or, When Is It The Best Time To Book On Line?, in Darin Lee (ed.), Advances in Airline Economics, Volume 2: The Economics of Airline Institutions, Operations and Marketing, Elsevier: Amsterdam, ch. 10:319-344.

[22] Staiger D. and Stock J. (1997). Instrumental Variables Regression with Weak Instruments. Econometrica, 65, 3:557-586.

[23] Stock J., Wright J. and Yogo M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. Journal of Business and Economic Statistics, 20, 4:518-529.

[24] Warnock-Smith D. and Potter A. (2005). An exploratory study into airport choice factors for European Low-Cost airlines. Journal of Air Transport Management, 11:388-392.

[25] Yuen Chi-Lock and Zhang A. (2008). Effects of competition and policy changes on Chines airport productivity: An empirical investigation. Journal of Air Transport Management, 1-9.

7 Appendix

Table 1: Descriptive statistics

	Year	Mean	S.D.	Min	Max
pax	2002	7789.90	13776.92	46.82	63000
	2005	9234.06	14964.93	452.13	68000
wlu	2002	8763.982	16439.79	46.82	77000
	2005	10270.22	17629.26	452.13	82000
tot rev	2002	91236.58	182934.1	3363	872025
	2005	105428.8	221920.3	5821.37	1075656
share other rev	2002	0.45	0.12	0.22	0.71
	2005	0.50	.11	0.23	0.85
share charge rev	2002	0.54	0.12	0.28	0.77
	2005	0.50	0.11	0.14	0.76
y	2002	4212.41	6568.01	15.30	30207.6
	2005	4924.95	7990.74	70.16	37607.3
k	2002	431381	946307.4	16739.5	4500000
	2005	581311	1586880	17741.5	7800000
l	2002	538.62	779.5	74	3628
	2005	577.8	861.2	95	4080
m	2002	39476.9	75247.92	2126.3	352633
	2005	43319.88	89976.35	1166	430000
pip	2002	0.36	0.24	0	0.88
	2005	0.47	0.21	0.13	0.89
ppt	2002	0.93	0.08	0.61	1
	2005	0.94	0.08	0.58	1

pax: thousands of passengers

wlu: thousands of work load units (see text)

tot rev: deflated total revenues (thousands of GB £)

share other rev: share commercial revenues on total revenues

share charge rev: share of charges revenues on total revenues

y: output measure in thousand of units.

k: monetary value of capital stock (thousands of GB £)

l: average employees

m: other variable inputs (thousands of GB £)

pip: percentage of international passengers

ppt: percentage of passenger traffic on wlu

Table 2 Ownership pattern

Heathrow	Priv
Gatwick	Priv
Stanstead	Priv
Southampton	Priv
Glasgow	Priv
Edinburgh	Priv
Aberdeen	Priv
Manchester	Pub
Bournemouth	Pub
Humberside	Pub
Nott-East Midlands	Pub
Birmingham	Mix
Newcastle	Mix
Belfast	Priv
Cardiff	Priv
Luton	Mix (1998-2005)
Blackpool	Pub (2002-2003); Mix (2004-05)
Bristol	Priv
Durham	Pub (2002); Priv (2003-05)
Exeter	Pub
Leeds-Bradford	Pub
Liverpool	Priv
London City	Priv
Norwich	Pub (2002-2003); Mix (2004-05)

Table 3: Average Share of Low-Cost Carriers' passengers

	2002	2003	2004	2005
$mkt1$	0.37 (0.40)	0.47 (0.43)	0.49 (0.44)	0.43 (0.41)
$mkt2$	0.36 (0.39)	0.41 (0.41)	0.40 (0.41)	0.40 (0.42)
$mkt3$	0.32 (0.09)	0.35 (0.13)	0.30 (0.14)	0.29 (0.15)
$mkt4$	0.42 (0.42)	0.57 (0.42)	0.61 (0.45)	0.63 (0.44)
$mkt5$	0.37(0.18)	0.57 (0.42)	0.35 (0.27)	0.38 (0.24)
$mkt6$	0.8 (-)	0.82 (-)	0.79 (-)	0.69 (-)

Note: Standard Deviation in parentheses

Mkt 1: Heathrow, Gatwick, Stansted, London City, Luton, and Southampton, Norwich;

Mkt 2: Manchester, Humberside, Nottingham, Birmingham, Blackpool, Leeds and Liverpool ;

Mkt 3: Glasgow, Edinburgh and Aberdeen;

Mkt4:Bournemouth, Cardiff, Bristol and Exeter;

Mkt 5: Newcastle and Durham; Mkt 6: Belfast.

Table 4 Two Step Regressions results

	TFP_1			TFP_2			TFP_3		
	OLS	CUE FE	LSDVC	OLS	CUE FE	LSDVC	OLS	CUE FE	LSDVC
TFP_{t-1}	0.92	0.20	0.75	0.99	0.24	0.34	0.94	0.02	0.22
	(0.02)	(0.21)	(0.20)	(0.02)	(0.16)	(0.17)	(0.05)	(0.91)	(0.16)
$LCCs$	0.17	0.76	1.03	0.18	0.81	1.02	0.26	1.04	2.40
	(0.05)	(0.36)	(0.48)	(0.05)	(0.37)	(0.68)	(0.09)	(0.49)	(1.04)
$dpriv$	0.01	-0.04	-.65	0.03	-0.15	-0.30	0.04	0.04	-0.06
	(0.08)	(0.26)	(0.33)	(0.08)	(0.21)	(0.35)	(0.12)	(0.22)	(0.50)
$dpub$	0.06	-0.06	0.48	0.09	-0.06	0.33	0.13	0.02	0.63
	(0.06)	(0.11)	(0.22)	(0.07)	(0.10)	(0.25)	(0.09)	(0.10)	(0.38)
pip	0.01	0.70	0.01	-0.12	0.54	-0.24	0.13	0.27	-0.35
	(0.20)	(0.41)	(0.46)	(0.17)	(0.40)	(0.60)	(0.28)	(0.35)	(0.92)
ppt	0.23	6.27	9.16	0.30	6.53	10.1	0.48	11.1	22.00
	(0.28)	(1.48)	(2.89)	(0.28)	(1.54)	(4.22)	(0.37)	(2.25)	(6.43)
$const$	-8.43	-	-	4.29	-		-17.2	-	-
	(37.3)	-	-	(39.6)	-		(70.6)	-	-
R^2	0.9	0.30	-	0.9	0.29	-	0.7	0.24	-
Hansen J. (p value)	-	0.92	-	-	0.95	-	-	0.51	-
Kleib. Paap	-	5.74	-	-	5.1	-	-	5.33	-

Notes

Markets-trend interaction dummies always included.

Reported standard errors are robust to heteroskedasticity and within unit autocorrelation of unknown forms.

Hansen's J Statistics is the Sargan-Hansen test for overidentifying restrictions (P values in parenthesis).

Kleibergen-Paap: weak identification test.