Airport Size and Urban Growth

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Abstract

This paper studies how airports affect economic growth in US metropolitan areas. The main finding is that airport size has a positive effect on local employment, with an elasticity of 0.04. The effect appears to be mostly due to a positive effect on services employment and to be concentrated in parts of the metropolitan area nearer the airport. To further understand how the airport affects the local economy, the effects on several other variables are estimated. Airport size is found to have positive effects on the number of firms, the population size, the rate of employment, and GDP in the local area. The magnitudes of the effects on population and employment suggest that airport expansion creates jobs for both existing residents and migrants to the area. The estimation uses a novel technique to identify the effects of airport infrastructure. It applies instruments for changes in airport size that are calculated from overall changes in air traffic in a set of categories: the airlines, the types of aircraft, or the distances flown. The technique could be adapted to study the effects of other types of infrastructure.

Keywords: Air travel, Transport infrastructure, Urban growth

JEL classification: H54, L93, R11, R42

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1 Introduction

Public spending on airports is motivated by the belief that improved air travel services will have a positive effect on economic growth in the areas that the airports serve. The public spending on airports can be substantial: in the US, federal, state, and local governments spend around $37 billion annually on airport infrastructure and operations.[1] The justification for this spending typically includes statements about the potential of a new or improved airport to attract firms and increase employment. However, there is little empirical basis for these claims. The purpose of this paper is to clarify what effects airports have on local economic activity.

The primary exercise I conduct in this paper is to estimate the effect of airport size on employment in US metropolitan areas. This effect is of obvious importance for policy evaluation but is challenging to estimate, in particular because the local economy is likely to affect airport size through the demand that it creates for air travel and the actions of policy makers. In addition, the local economy and air traffic may both be affected by external factors or past events. An observed relationship between airport size and economic outcomes is therefore likely to reflect factors other than the causal effect of airports that is of interest.

To measure the causal effect of a change in airport size on the local economy, it is necessary to find a source of variation in airport size that is not driven by or correlated with other factors for local economic outcomes. This is difficult in the case of airports because actual decisions about airport improvements are usually made in response to local factors, the cost of airport construction precludes conducting experiments, and air travel is not strongly dependent on external factors that vary by location such as physical geography or climate. The approach I adopt is to construct a set of instruments for changes in the traffic at each airport that are plausibly unrelated to other factors for economic outcomes. I then compare the changes in airport size explained by the instruments with changes in local economic outcomes to produce estimates of the causal effects of airports.

The instruments are constructed using a technique similar to that proposed by Bartik (1991) to generate quasi-experimental variation in local employment. Each instrument is constructed by taking the amount of local air traffic in a certain category, then applying the national rate of

[1] The annual budget of the Federal Aviation Administration is currently around $16 billion, which is used to fund airport construction and maintenance, operations, and research and development (United States Department of Transportation, 2016). This is complemented by around $21 billion in spending by state and local governments (United States Census Bureau, 2014).

growth of that category to the local area. The sets of categories used are the airlines, the aircraft types, and a set of distance ranges. The estimation uses the amount of traffic as the measure of airport size, which is intended to reflect the physical size of the airport but also the convenience of travel. The findings therefore apply to any policies that attract airlines to operate at an airport, even if not associated with improvements in physical infrastructure.

Airport size is found to have a positive effect on local employment, with an elasticity of 0.04. This means that in a typical metropolitan area with one million residents, a 10% increase in air traffic leads to the creation of around 1,660 new jobs.[2] Furthermore, the effect on local employment is driven by changes in particular sectors. Industry-level estimates show that airport size has large positive effects on employment in some types of services and in construction, but no measurable effect on employment in manufacturing, wholesale and retail trade, or transport and utilities.

I also find positive effects of airport size on a range of other local outcomes including the number of firms, population size, the employment rate, and GDP. The magnitudes of these effects suggest that airport expansion leads to increased employment for existing residents while also inducing migration to the local area. There is no measurable effect on wages, suggesting either that labour supply in the relevant sectors is sufficiently elastic that employment can adjust without a substantial increase in wages, or that the amenity value of airports causes the supply of labour to expand when an airport is improved. The effect of airport size on GDP is positive and around the same magnitude as the effect on employment, so there is no evidence of output per worker being affected by airport size.

To understand how the effects on the local economy depend on proximity to the airport, I study the relationship between airport size and employment in different locations within a metropolitan area. Airport size correlates with employment in all parts of the metropolitan area, but the causal effect of airports is concentrated in the parts of the metropolitan area that are nearer the airport. These results suggest that either local air traffic is affected by demand from the entire metropolitan area or both air traffic and employment are affected by some common factors, but that new jobs created by airport improvements are concentrated near the airport.

This paper makes two main contributions to the existing literature. The first is to quantify

[2] In 2015, employment was 41.5% of the population of the sample metropolitan areas, so a 'typical' metropolitan area with one million residents would have around 415,000 people employed. A 10% increase in airport size would therefore increase employment by $10\% \times 0.04 \times 415,000 \simeq 1,660$.

the effects of airport expansion on local employment and other economic outcomes. Despite the vast amount of public money that is spent on airports, relatively little evidence has been presented of their effects. Green (2007) and Blonigen and Cristea (2015) estimate the effect of airport size on local economic growth and find positive effects, with magnitudes somewhat larger than the estimates in this paper. The difference in the results could be explained by the technique applied in this paper having less potential to be biased due to the airport size and economic outcomes being simultaneously determined. McGraw (2016) tests whether small cities with airports grow faster than those without airports and also finds a positive effect. Brueckner (2003) and Sheard (2014) estimate the effects of airports on particular sectors and find that the effects are most pronounced for service industries, which is consistent with the results presented here. Campante and Yanagizawa-Drott (2016) estimate the effects of long-range flights on business connections and economic growth and find strong positive effects.

The second main contribution of this paper is to present a novel method for estimating the causal effects of airports and other types of transport infrastructure. The previous literature uses a variety of techniques, most often applying geographical or historical variables as instruments. Brueckner (2003) and Green (2007) use the distance to the midpoint of the US to instrument for airport size, as geographical centrality increases the potential of a city as an airline hub.[3] Sheard (2014) uses the 1944 National Airport Plan and McGraw (2016) uses the 1922 Army air network and 1938 Air Mail routes to instrument for current airports, as the locations of airports are highly persistent.[4] Another approach is to measure the effects of airports using differences in traffic either side of a policy or functional discontinuity. Brueckner (2003) uses hub status to instrument for airport size, as this implies a larger number of incidental travellers. Blonigen and Cristea (2015) use the 1978 deregulation of US air travel to explain variation in air traffic levels. Campante and Yanagizawa-Drott (2016) use a discontinuity in flight distances due to regulatory requirements and the ranges of aircraft.[5]

The method I propose has several advantages over the available alternatives, at least for the

[3]Physical geography has more potential for explaining roads and railways, as these types of infrastructure require unbroken and relatively straight paths of flat terrain. Thus Duranton and Turner (2012) and Duranton, Morrow and Turner (2014) use early exploration routes and 1898 railways to instrument for current roads and highways.

[4]A similar approach was taken to study the effects of roads and highways by Baum-Snow (2007), Michaels (2008), Duranton and Turner (2012), and Duranton, Morrow and Turner (2014), who use the 1944 or 1947 National Highway Plan to instrument for current roads.

[5]Studies of other types of transport infrastructure use a broader range of identification techniques. Redding and Turner (2015) present a detailed summary.

study of airports. Firstly, it is relatively simple to implement as it does not require detailed historical data or the identification of a particular type of policy. It simply requires that the level of infrastructure can be represented by its level of traffic and that the traffic can be divided into categories that are influenced by factors common to many locations. Secondly, as the instruments are driven by structural variation in the air travel network rather than variation around a hand-chosen discontinuity, the method does not rely on arguments that for example a particular policy decision is exogenous to the outcomes being studied. Thirdly, I show that the method is relatively powerful in terms of the amount of variation in airport sizes that it explains. Fourthly, the method may be more informative for some types of policy analysis as it allows short-term effects of changes in infrastructure to be measured, whereas effects explained by geography or historical decisions may take decades to accumulate.

The remainder of this paper is arranged as follows. The model is outlined in Section 2. The data and the method used to construct the instruments are described in Section 3. The results of the estimation are presented in Section 4. Concluding remarks are presented in Section 5. Various alternative specifications, details of the instruments, and robustness checks are presented in the appendices.

2 Model

This section outlines the model that is used as the basis for the estimation. The model is a simple representation of how the instruments relate to airport size and how airport size affects local economic outcomes. For clarity the model is explained only in terms of the effect of airport size on employment, though it is also used to estimate the effects on other outcome variables.

2.1 Local employment

The combined size of the airports in metropolitan area m at time t is denoted $A_{m,t}$ and is measured using the amount of traffic. A larger airport may benefit workers in the local area through an effect on the productivity of local firms and thereby wages, or by providing a direct amenity benefit. The productivity benefit may arise because the airport provides access to markets where local firms can source inputs and sell products. This is reflected in the wages earned by local workers, which are a function $w(A_{m,t})$ of the airport size. The amenity benefit would arise because more convenient travel increases the utility of local residents, which is represented in money-metric terms by the function $g(A_{m,t})$.

The population in the metropolitan area is constrained by the costs of housing and commuting, which are increasing in the number of local residents. The cost of living in metropolitan area m at time t is described by the function $c\left(N^{\star}_{m,t}\right)$, where $c' > 0$ and $N^{\star}_{m,t}$ is the natural level of employment.

Individuals gain utility from consumption and the amenity value of air travel. As utility is increasing in consumption, in equilibrium the budget constraint must bind, so the amount spent on consumption is equal to the wage income less the cost of living. The factors besides the airport that determine wages, the cost of living, and amenities are combined in the local factors μ_m and time-specific factors ν_t. The utility of an individual in metropolitan area m at time t is thus:

$$U = w(A_{m,t}) - c\left(N^{\star}_{m,t}\right) + g(A_{m,t}) + \mu_m + \nu_t \tag{1}$$

Individuals are assumed to be able to migrate freely between metropolitan areas and to obtain the reservation utility $\bar{U}$ if they live elsewhere. In equilibrium, the level of utility must therefore equal $\bar{U}$. The utility function (1) and migration condition thus imply:

$$w(A_{m,t}) - c\left(N^{\star}_{m,t}\right) + g(A_{m,t}) + \mu_m + \nu_t = \bar{U} \tag{2}$$

According to (2), the number of employees in the metropolitan area is determined by the relationship between wages, the cost of living, local amenities, and opportunities elsewhere. A change in airport size may affect employment through either wages or amenities. The cost of living changes when the population adjusts, which restores the equilibrium.

The functional forms $w(A) \equiv \kappa_w \ln(A)$, $g(A) \equiv \kappa_g \ln(A)$, and $c(N) \equiv \ln(N)$ are assumed for the respective functions. The term $\bar{x}$ is set to zero as it can be captured in the fixed effects μ_m and ν_t, the magnitudes of which are not ultimately of interest. Making these substitutions in (2) yields an expression for the natural level of employment $N^{\star}_{m,t}$ in metropolitan area m at time t:

$$N^{\star}_{m,t} = e^{\mu_m + \nu_t} A^{\kappa}_{m,t} \tag{3}$$

The term $\kappa \equiv \kappa_w + \kappa_g$ in (3) captures the combined effect of the productivity and amenity mechanisms. It would be difficult to separate these directly in the estimation without introducing control variables (such as wages) that would be endogenous or imposing an overly restrictive structure. Instead, I estimate the effects of airport size on employment, total output (GDP), and wages, then compare the sizes of the coefficients to infer whether productivity is affected.

2.2 Growth in the local economy

The actual level of employment in metropolitan area m at time t is denoted $N_{m,t}$. The level of employment changes based on the difference between the current level $N_{m,t}$ and the natural levels over the period from t to $t+1$ according to the following convergence condition:

$$N_{m,t+1} = N_{m,t}^{\star\lambda_1} N_{m,t+1}^{\star\lambda_2} N_{m,t}^{1-\lambda_1-\lambda_2} \tag{4}$$

Employment at time $t+1$ depends on employment in the previous period, so $1-\lambda_1-\lambda_2 > 0$, and converges towards the natural level of employment, so $\lambda_1, \lambda_2 \geq 0$ and $\lambda_1 + \lambda_2 > 0$. The following substitutions simplify the algebra:

$$\gamma_{2,m} \equiv (\lambda_1 + \lambda_2)\,\mu_m$$

$$\delta_{2,t} \equiv \lambda_1 \nu_t + \lambda_2 \nu_{t+1}$$

$$\beta_2 \equiv -(\lambda_1 + \lambda_2)$$

$$\alpha_2 \equiv -\beta_2 \kappa$$

$$\theta \equiv -\lambda_2 \frac{\alpha_2}{\beta_2}$$

Substituting (3) into (4) yields the following relationship between the growth rates of employment and airport size over the period from t to $t+1$:

$$\frac{N_{m,t+1}}{N_{m,t}} = e^{\gamma_{2,m}+\delta_{2,t}} A_{m,t}^{\alpha_2} N_{m,t}^{\beta_2} \left(\frac{A_{m,t+1}}{A_{m,t}}\right)^{\theta} \tag{5}$$

Taking logs of both sides of (5) and introducing the notation $a = \ln(A)$ and $n = \ln(N)$:

$$n_{m,t+1} - n_{m,t} = \alpha_2 a_{m,t} + \beta_2 n_{m,t} + \theta \left[a_{m,t+1} - a_{m,t}\right] + \gamma_{2,m} + \delta_{2,t} \tag{6}$$

Equation (6) is the relationship between changes in local airport size and employment that is to be estimated. As the changes in local air traffic $a_{m,t+1} - a_{m,t}$ are likely influenced by variation in local employment $n_{m,t+1} - n_{m,t}$, I instrument for the change in airport size using variables that explain changes in local air traffic but are plausibly not otherwise correlated with local employment.

2.3 Structural changes in the air travel network

The instruments reflect changes in air traffic that are driven by overall changes in the air travel network. The instruments are expressed in terms of the notional level of air traffic at time $t+1$, denoted $\hat{A}_{m,t+1}$, that would arise given these overall changes and the actual level of traffic at time t. Using $\gamma_{1,m}$ and $\delta_{1,t}$ to denote factors specific to the metropolitan area and time, respectively, the growth in air traffic explained by the instrument is assumed to satisfy:

$$\frac{A_{m,t+1}}{A_{m,t}} = e^{\gamma_{1,m}+\delta_{1,t}} A_{m,t}^{\alpha_1} N_{m,t}^{\beta_1} \left(\frac{\hat{A}_{m,t+1}}{A_{m,t}}\right)^{\eta} \tag{7}$$

The term $\frac{\hat{A}_{m,t+1}}{A_{m,t}}$ in (7) is the instrument for the growth in air traffic, the derivation of which is detailed below. Airport size and employment at time t are included in (7) to capture systematic differences in how airports tend to grow depending on their size or the overall size of the metropolitan area. For example, it may be costly to maintain or expand a large airport, constraining its growth, or large airports grow more rapidly due to increasing returns to scale. Taking logs of both sides of (7) and again using $a = \ln(A)$ and $n = \ln(N)$:

$$a_{m,t+1} - a_{m,t} = \alpha_1 a_{m,t} + \beta_1 n_{m,t} + \eta \left[\hat{a}_{m,t+1} - a_{m,t}\right] + \gamma_{1,m} + \delta_{1,t} \tag{8}$$

2.4 Estimation equations

The system of equations I estimate is derived from (6) and (8):

$$a_{m,t+1} - a_{m,t} = \alpha_1 a_{m,t} + \beta_1 n_{m,t} + \eta \left[\hat{a}_{m,t+1} - a_{m,t}\right] + \gamma_{1,m} + \delta_{1,t} + \varepsilon_{1,m,t} \tag{9}$$

$$n_{m,t+1} - n_{m,t} = \alpha_2 a_{m,t} + \beta_2 n_{m,t} + \theta \left[a_{m,t+1} - a_{m,t}\right] + \gamma_{2,m} + \delta_{2,t} + \varepsilon_{2,m,t} \tag{10}$$

The main coefficient of interest is θ, which represents the effect of a change in airport size on the change in employment. As both airport size and employment are expressed in logs in (10), the coefficient θ is an elasticity.

The equations (9) and (10) are estimated using periods of one year (from t to $t+1$). Though it is reasonable to expect that the effects on employment would accrue over a longer period, I test the relationship with additional past rates of growth in airport size and with periods of longer than one year. The results suggest that the effect on employment is captured almost entirely by the one-year changes.

For the system of equations (9) and (10) to be identified, the following conditions must be satisfied:

$$\eta \neq 0 \tag{11}$$

$$Cov\left(\hat{a}_{m,t+1} - a_{m,t}, \varepsilon_{2,m,t}\right) = 0 \tag{12}$$

Condition (11) is the relevance condition, which requires that the instruments explain a significant amount of the variation in airport sizes, conditional on the controls. This condition is tested statistically as part of the estimation.

Condition (12) is the exogeneity condition or exclusion restriction. It requires the instrument to affect changes in employment only through changes in airport size. While there is no statistical test for the exclusion restriction, I present three types of evidence in support of it. Firstly, in the description of the instruments, I detail why it is reasonable to believe that the condition holds. Secondly, I run overidentification tests that demonstrate that the second-stage residuals are indeed uncorrelated with the overidentifying instruments under the assumption that one of the instruments is valid. Thirdly, the tests of how airports affect employment by location within the metropolitan area suggest that the correlation between airport size and employment and the measured effect of airport size on employment are due to different sets of jobs.

The control variables $a_{m,t}$ and $n_{m,t}$ in (9) and (10) are intended to account for systematic differences in airport and employment growth that correlate with the initial values. For example, an airport that is small relative to local employment may tend to expand more quickly. The use of the controls raises a potential concern, however, because if the estimate of α_2 or β_2 is biased, then the coefficient on the change in airport size θ would also be biased. It is therefore not clear a priori whether these controls should be included. Nevertheless, the estimate of θ is shown in Appendix A2 to be practically identical with or without each of the controls.[6]

The fixed effects $\gamma_{1,m}$ and $\gamma_{2,m}$ account for separate linear time trends for each metropolitan area and the year fixed effects $\delta_{1,t}$ and $\delta_{2,t}$ capture economy-wide changes in airport size and employment over time. These fixed effects are included to address some obvious concerns about the estimation. For example, if changes in overall US employment influenced overall US air traffic and thereby the instruments, then the exclusion restriction would be violated. The year fixed effects should capture such macroeconomic variation. The results in Appendix A2 indicate that both types of fixed effects capture a substantial amount of variation. A number of other issues with the estimation are addressed in the robustness checks in Appendix A4.

3 Data

The dataset used for the analysis is an annual panel of US air traffic and economic variables for the period from 1991 to 2015. The variables are assembled from several sources and aggregated by Core Based Statistical Area (CBSA) according to the December 2009 definitions. The CBSAs are defined by the Office of Management and Budget as distinct sets of counties, with each CBSA representing an urban core and the surrounding areas with which it is integrated by commuting.

The data on air travel are mostly from the T-100 segment data from the US Bureau of Transportation Statistics (BTS). These data detail air traffic by airport pair, airline, type of aircraft, and month for all flights with at least one endpoint at a US airport.

[6] In addition, Wooldridge (2012, ch. 12) notes that the problems that arise from including lagged dependent variables as controls are fundamentally a matter of the model being correctly specified. The controls for $a_{m,t}$ and $n_{m,t}$ are justified by basic processes of convergence but it is less apparent why further past values should be meaningful.

The economic variables include various measures of employment as well as population size, personal income per capita, GDP, and an index of house prices. The employment data are from the County Business Patterns, which details the number of firms, number of employees, and aggregate payroll by year, county, and industry. The County Business Patterns do not include information about employment in public administration, so those workers are not included in the numbers of employees stated in the remainder of this paper.[7] The population data are from the US Census Bureau, which measures the population every ten years and produces annual estimates of the population by county for all years in between. The personal income per capita is from the USA Counties database. The GDP measure is based on the annual state-level estimates published by the Bureau of Economic Analysis (BEA). These state-level figures are apportioned to the counties within each state according to the contemporary shares of aggregate payroll in the County Business Patterns, then aggregated by CBSA. The house price index is from the Federal Housing Finance Agency.

As the estimation compares yearly changes in air traffic and economic outcomes, the timing of the variables is crucial. The employment data in the County Business Patterns are measured in the week including the 12th of March of the given year, while the US Census is typically measured at the beginning of April. To make the timing of the variables consistent and allow clearer interpretation of the results, the air traffic figures are aggregated to years ending on March 31st. That is, the air traffic for '1991' is the traffic from April 1st, 1990 to March 31st, 1991. Year-on-year changes in air traffic are thus compared with employment at the end of the year, with longer-term effects investigated by adding past rates of growth in air traffic. Where necessary, the GDP and other outcome variables are adjusted to reflect the levels at the end of March.[8]

The sample is limited to the contiguous United States: the District of Columbia and all states except for Alaska and Hawaii.[9] The sample includes only airports that hosted at least 2,500 departing passengers – the threshold specified by the Federal Aviation Administration

[7]There is no equivalent source of annual data on employment in public administration by county that goes as far back as the early 1990s. However, data for recent years from the American Community Survey indicate that public administration represents around 5% of employment in the CBSAs in the sample.

[8]The state-level GDP data from the BEA are apportioned using payroll in March from the County Business Patterns. The population and other variables from the US Census are currently measured around April 1st.

[9]Alaska and Hawaii are excluded because they have few metropolitan areas and the role of aviation in those states is substantially different from its role elsewhere in the US.

(FAA) for a *Commercial Service Airport* – in all years from 1991 to 2015.[10] CBSAs with no such airports are excluded and for those with multiple airports the CBSA-level air traffic is found by summing the traffic at all facilities.[11] This yields a sample of 181 CBSAs with a total of 198 airports.[12] The period of the sample is 1991 to 2015 as this is the longest span of time for which the data are available.[13] Figure 1 presents a map of the CBSAs and airports in the sample and Table 1 presents summary statistics for the main variables in the dataset.

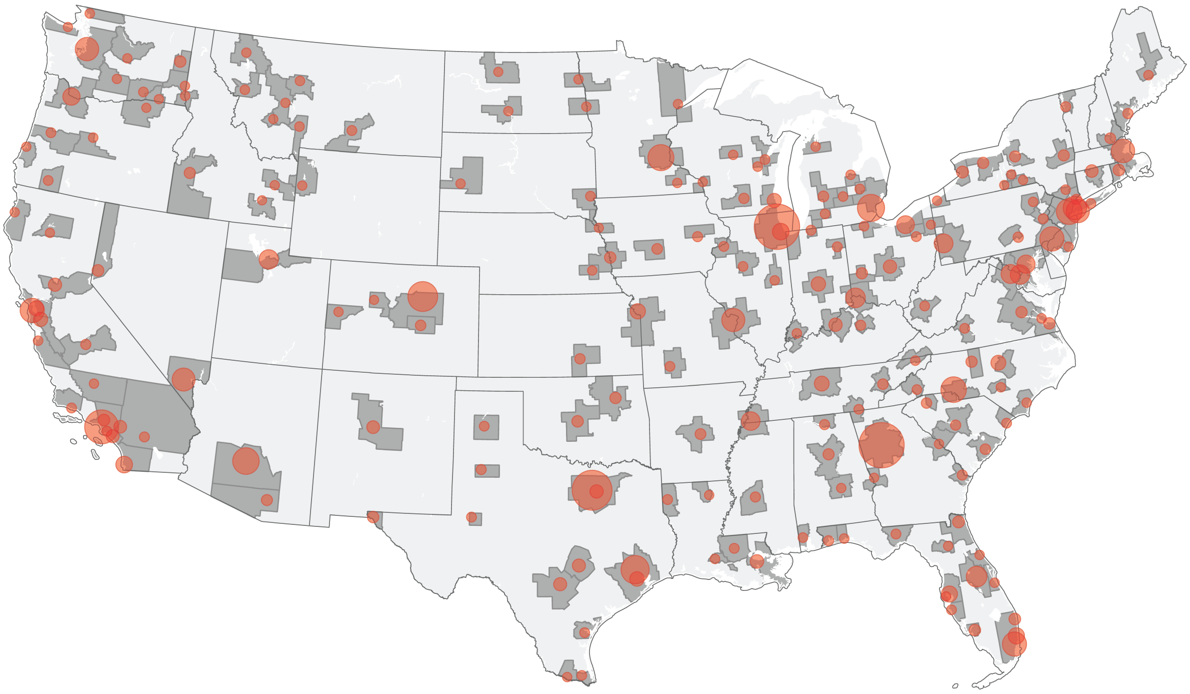

Figure 1: Map of the CBSAs and airports in the sample. The shaded areas of land represent the sample CBSAs. The shaded circles represent the sample airports, with the diameter of each circle proportional to the aggregate number of flights from 1991 to 2015.

[10]Denver International Airport opened in 1995 and Austin–Bergstrom International Airport opened in 1999 as replacements for the main airports serving those cities. In each case the former airport was closed and its airport code reassigned to the new airport. These airports are included in the sample and treated as continuously-operating airports.

[11]Brueckner, Lee and Singer (2014) find that the appropriate level of aggregation for passenger air-travel markets is the city, rather than the airport. Sheard (2017) finds that the level of traffic in a metropolitan area depends on the number of airports. To avoid complications from airports being added or removed during the period of the sample, only airports that meet the minimum traffic threshold for all years are included.

[12]The minimum of 2,500 departing passengers in all years excludes 1,014 of the 1,212 commercial airports that operated in CBSAs in the contiguous United States between 1991 and 2015. However, as the excluded airports are generally relatively small, they represent only 3.7% of the flights and 1.0% of the passengers at airports in CBSAs in the contiguous United States.

[13]The T-100 air traffic data are available from January 1990 and the most recent edition of the County Business Patterns is for 2015.

	Mean	Std. dev.	Minimum	Maximum
Population	1,108,893	2,034,463	15,522	19,445,705
Number of employees	458,822	849,222	5,520	8,138,014
Mean wage ($'000)	32.24	9.33	13.83	109.96
Personal income per capita ($'000)	30.42	9.69	9.79	122.17
Number of firms	28,107	54,241	794	556,656
Gross domestic product (GDP) ($'bn)	49.59	112.51	0.22	1,555.73
Number of airports	1.09	0.44	1	5
Number of departing flights	44,489	87,486	112	652,151
Number of seats on departing flights	4,965,638	10,772,819	4,782	74,370,488
Number of departing passengers	3,460,383	7,711,516	2,799	59,582,356

Note: 4,525 observations of each variable, in a balanced panel of 181 CBSAs

Table 1: Summary statistics for the main variables in the data.

The principal measure used for airport size is the number of passenger flights that depart from airports in the CBSA. This variable measures the physical amount of infrastructure indirectly and represents the practical convenience of the airport for a potential passenger, as it is a product of the number of destinations and the frequency of flights to those destinations. Nevertheless, the number of flights correlates with basic measures of physical airport size, as shown in Sheard (2014). The decision to measure airport size with air traffic is also motivated by the lack of detailed information about the physical features of an airport, the difficulty of quantifying these features, and the greater relevance of air traffic to the construction of the instruments.

Three alternative measures of airport size are also used: the number of seats on departing flights, the number of departing passengers, and a measure of 'air access'. The air access variable weights the number of flights to each destination airport by the contemporary population of the metropolitan area – whether in the US or abroad – that it serves. US destinations use the CBSA populations from the US Census. Canadian destinations use populations by census metropolitan area (CMA) and census agglomeration (CA) from Statistics Canada. For other countries, the data are from the UN World Urbanization Prospects, which includes metropolitan areas with populations of at least 300,000 and the capital cities of sovereign states. Destinations that do not meet the respective definition are not included in the measure of air access.

3.1 Instruments

The instruments I use for changes in air traffic are adapted from the Bartik (1991) instruments for local economic growth. The instruments are constructed by dividing up the traffic at each airport at the beginning of a period by a set of categories, for example the airlines, then applying the national rate of growth over the period for each category to the initial traffic in that category at the airport. This produces an instrument for the change in airport size at each location that is driven by overall changes in the air travel network, but is unrelated to local changes that could influence air traffic in a given period.

I apply five separate instruments that are constructed using the following sets of categories (henceforth "categorizations") for air traffic: (1) the airlines that operate the flights, (2) the aircraft models, (3) the aircraft classes (based on engine type and fuselage size), (4) a set of ranges for the number of seats in the aircraft, and (5) a set of ranges for the distance of the flight. The categories are listed in Appendix A1. The instruments are constructed by dividing up the air traffic in a metropolitan area by one of the categorizations, then calculating what the traffic would be at the end of the period if the traffic in each category in a CBSA increased at its national rate of growth.

Formally, the instrument for the change in air traffic in metropolitan area m over the period from t to $t+1$ is represented by the notional level of traffic $\hat{A}_{m,t+1}$ at the end of the period. Its value is calculated using the following formula, in which $c \in C$ indexes the categories and $A_{c,m,t}$ is the amount of air traffic in metropolitan area m at time t that is in category c:

$$\hat{A}_{m,t+1} = \sum_{c} A_{c,m,t} \left(\frac{\sum\limits_{n \neq m} A_{c,n,t+1}}{\sum\limits_{n \neq m} A_{c,n,t}} \right) \tag{13}$$

The term $A_{c,m,t}$ on the right-hand side of (13) is the initial level of traffic in category c and the term in parentheses is the overall growth rate for category c over the period. The overall growth rate is calculated separately for each CBSA, excluding traffic that originates or terminates in that CBSA. This is done to avoid a potential problem with the exclusion restriction: the traffic at a given airport is part of the national level of traffic, so if local traffic is affected by changes in local employment, then local employment would partly determine the instrument.[14] Figure 2 illustrates the networks for two example categories and highlights the flights that would be excluded for the Detroit-Warren-Livonia, MI CBSA.

[14]When using Bartik instruments for changes in employment, this concern is typically addressed by the small spatial unit assumption. That is, if employment is aggregated to the county level, then the contribution of any one county to overall employment for that industry is small. This assumption would not be expected to hold for air travel due to the concentration of aircraft operations at large airports.

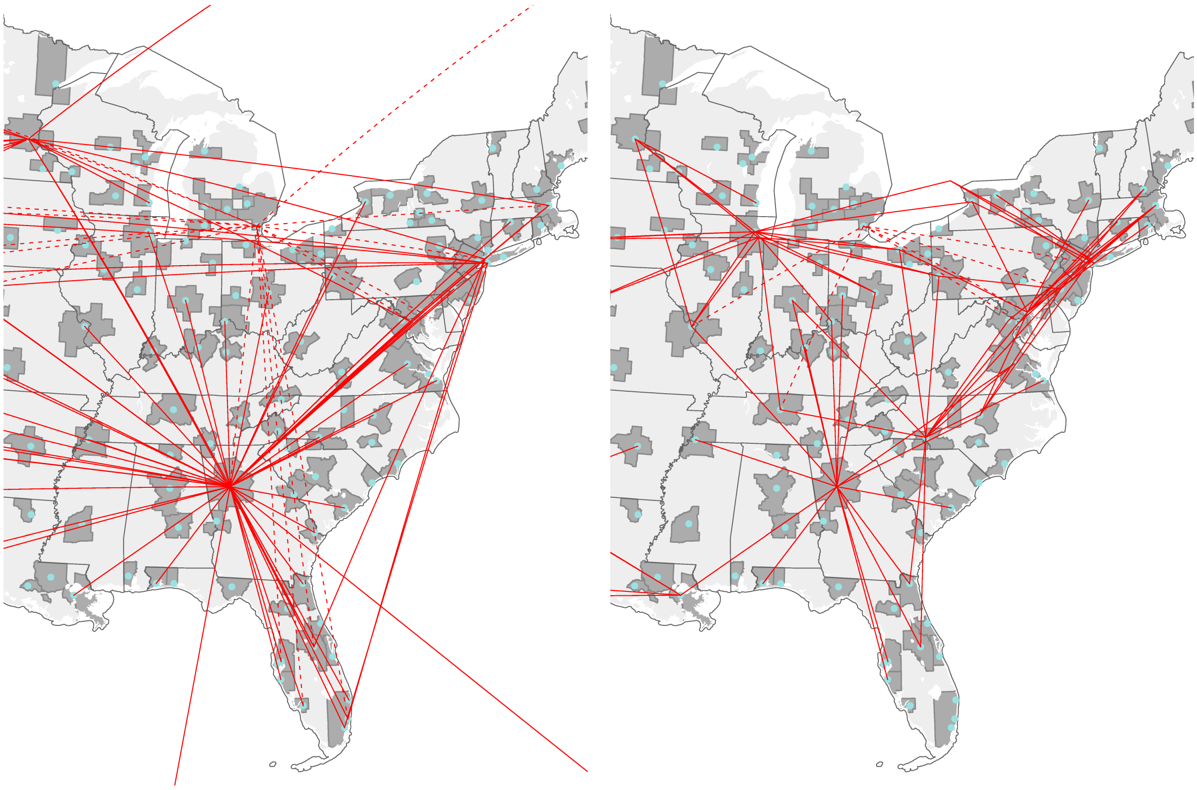

Figure 2: Networks of flights for two example categories in 2010: routes operated by Delta Air Lines (on the left) and routes between 250 and 500 miles in length (on the right). For clarity, each map only includes routes with 1,000 or more daily passengers. The dots represent airports in the sample and the lines represent the routes. To calculate the overall growth rate applied to a CBSA, the routes to and from that CBSA are excluded. As an example, the routes excluded for the Detroit-Warren-Livonia, MI CBSA are illustrated with dashed lines.

When air traffic is measured as the number of flights, seats, or passengers, the instruments are calculated from the local levels and overall growth rates of the same measure. With the 'air access' measure, the instrument is calculated by applying the overall growth rates to the number of flights on each route.

The principle underlying the instruments is that growth rates in the categories are unrelated to CBSA-specific changes in economic conditions. With the 'airline' instrument, the part of the variation in local air traffic that is determined by overall growth in an airline's traffic should not be driven by changes in the local economy, especially when local traffic is excluded from the calculation of the overall growth rate. Rather, an airline's overall level of traffic should influence its traffic at individual airports through determinants of its overall demand and productivity such as operational innovations, marketing, and labour relations. When the demand or productivity of an airline increases, it will tend to increase traffic at airports where it already operates, as it has gates, slots, hangar space, and employees at those facilities.[15]

[15]The airline industry featured several large mergers during the period of the data. For mergers where the traffic

Similar reasoning applies to the categorizations based on the type of aircraft: the model, class, and number of seats. Each type of aircraft is constrained to operating at airports with facilities such as runways, aprons, hangars, and terminals capable of handling it. If the operations of a particular type of aircraft are increased, then the new flights will tend to be at airports that already host that type of aircraft. Furthermore, the variation in traffic at an airport explained by the overall traffic of the aircraft it hosts could not be influenced by local factors.

The instrument based on distance ranges is intended to reflect overall changes in aircraft technology and the methods of operating the air travel network, such as changes in the ranges of aircraft, the prevalence of short- and long-haul flights, and the routing of traffic through hubs. Given that local traffic is excluded from the calculation of the overall growth rates, this could not be driven by economic conditions in the local area.

The number of seats and the distance flown are quantitative variables. Moreover, substitution between similar distances would be possible to some degree, so their levels should be related. Thus the observed growth rates for these variables are smoothed across the category ranges for each CBSA and time span.[16]

The essential qualities of an instrument are that it satisfy the relevance condition (11) and the exclusion restriction (12). The relevance condition (11) is straightforward to test statistically as it simply requires a significant relationship between the instruments and changes in airport size, given the controls, and all of these variables are known. The results presented below demonstrate that each of the instruments exceeds a reasonable threshold for the relevance condition to be satisfied.

The exclusion restriction requires that an instrument only be related to changes in employment or the alternative outcome variable through its effect on the level of air traffic. This condition would be violated if the instrument were correlated with other factors that affect the outcome variable, or if it were partly determined by the outcome variable. Both possibilities appear unlikely given how the instruments are constructed. Apart from the variation in airport sizes explained by the instrument, there is no clear channel through which the concentrations of

of the airlines is combined under a single code, the 'airline' instrument for any time period that overlaps the merger is calculated using the overall growth rate in the combined entity. The method is detailed and the relevant mergers are listed in Appendix A1.

[16]Where the observed value for the growth rate in category c is g_c and the number of observations is n_c, the smoothed value $\tilde{g}_c$ is calculated as $\tilde{g}_c = \frac{n_{c-1}g_{c-1}+2n_c g_c+n_{c+1}g_{c+1}}{n_{c-1}+2n_c+n_{c+1}}$.

certain airlines or aircraft at an airport could influence local growth. There is a concern that certain airlines or types of aircraft may operate in parts of the country with stronger employment growth. However, the results are shown in Appendix A4 to be robust to the inclusion of state or regional fixed effects for each year.

The fact that the variation in the instruments is driven by overall growth rates, where these growth rates are calculated excluding traffic in the local area, eliminates the possibility of exogenous changes in local employment being reflected in the instruments in the same period. If these exogenous changes in employment are correlated between periods, then there is a concern that the instruments could be correlated with employment through the initial employment levels $A_{c,m,t}$ in (13) being updated in each period. This issue is studied in Appendix A3, which applies instruments calculated using category shares that are fixed in 1991. The results are shown to be broadly consistent with those generated using category shares that are updated in each period.

4 Estimation

The results from the ordinary least squares (OLS) estimation of (10) are presented in Table 2. These results show how changes in airport size $A_{m,t}$ are correlated with changes in local employment.

Columns 1 to 6 of Table 2 use different sets of the fixed effects and independent variables in equation (10) to demonstrate how the estimation is affected by these variables. All of these regressions use the number of flights as the measure of airport size. Column 1 shows the estimates with no fixed effects or controls, Column 2 uses CBSA fixed effects, Column 3 uses year fixed effects, and Column 4 includes both CBSA and year fixed effects. Columns 5 and 6 add the controls for initial log airport size and initial log employment. Column 6 is my preferred specification, which includes all of the variables in (10) and uses the number of flights as the measure of airport size.

The remaining columns of Table 2 use alternative measures of airport size. Columns 7 and 8 use the number of seats on departing flights and the number of departing passengers, respectively. Column 9 uses the air access measure, which weights the number of flights by the populations of the destination metropolitan areas.

Airport-size measure	(1) OLS Flights	(2) OLS Flights	(3) OLS Flights	(4) OLS Flights	(5) OLS Flights	(6) OLS Flights	(7) OLS Seats	(8) OLS Pass.	(9) OLS Air access
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.023^a	0.023^a	0.012^a	0.011^a	0.008^a	0.011^a	0.014^a	0.016^a	0.007^a
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.002)
$\ln(A_{m,t})$					-0.006^a	-0.003^c	-0.002	-0.002	-0.003^b
					(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$\ln(emp_{m,t})$						-0.074^a	-0.073^a	-0.073^a	-0.072^a
						(0.008)	(0.009)	(0.008)	(0.008)
R^2	0.02	0.10	0.39	0.47	0.47	0.50	0.50	0.50	0.50
CBSA fixed effects		Y		Y	Y	Y	Y	Y	Y
Year fixed effects			Y	Y	Y	Y	Y	Y	Y

Note: 4,344 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; *a*, *b*, *c* denote significance at 1%, 5%, 10%

Table 2: OLS estimation of the relationship between airport size and employment.

The coefficients on $\ln(A_{m,t+1}) - \ln(A_{m,t})$ in Table 2 demonstrate a clear, positive relationship between changes in airport size and employment. This is not surprising, as a larger population means more potential travellers. One would expect air traffic to be positively affected by demand for trips and indeed Rupp and Holmes (2006) show that airlines even cancel significantly fewer flights on days of the week with higher demand for tickets. It is therefore not possible to infer a causal effect of airports on employment from the OLS coefficients in Table 2.

To measure the causal effect of air traffic on local employment, I estimate the system (9) and (10) using two-stage least squares (TSLS) and the instruments detailed above. The first stage of the TSLS estimation establishes the relationship between the instruments and the changes in airport size in (9). The results are displayed in Table 3, with each column using a different set of instruments. All columns of Table 3 use the full specification of (9) and use the number of flights as the measure of airport size.

Airport-size measure	(1) OLS Flights	(2) OLS Flights	(3) OLS Flights	(4) OLS Flights	(5) OLS Flights	(6) OLS Flights	(7) OLS Flights	(8) OLS Flights	(9) OLS Flights
$\ln\left(\hat{A}_{m,t+1}\right) - \ln\left(A_{m,t}\right)$	0.181^{a}					0.162^{a}	0.166^{a}		0.159^{a}
(‘airline’ instrument)	(0.048)					(0.043)	(0.042)		(0.041)
$\ln\left(\hat{A}_{m,t+1}\right) - \ln\left(A_{m,t}\right)$		0.149^{a}							
(‘aircraft model’ instrument)		(0.038)							
$\ln\left(\hat{A}_{m,t+1}\right) - \ln\left(A_{m,t}\right)$			0.485^{a}			0.426^{a}		0.368^{a}	0.329^{a}
(‘aircraft class’ instrument)			(0.067)			(0.058)		(0.062)	(0.062)
$\ln\left(\hat{A}_{m,t+1}\right) - \ln\left(A_{m,t}\right)$				0.734^{a}					
(‘seats’ instrument)				(0.135)					
$\ln\left(\hat{A}_{m,t+1}\right) - \ln\left(A_{m,t}\right)$					0.844^{a}		0.728^{a}	0.420	0.355
(‘distance’ instrument)					(0.215)		(0.203)	(0.262)	(0.250)
$\ln\left(A_{m,t}\right)$	-0.210^{a}	-0.205^{a}	-0.218^{a}	-0.218^{a}	-0.205^{a}	-0.218^{a}	-0.206^{a}	-0.213^{a}	-0.214^{a}
	(0.024)	(0.023)	(0.023)	(0.023)	(0.022)	(0.024)	(0.023)	(0.021)	(0.022)
$\ln\left(emp_{m,t}\right)$	0.232^{a}	0.229^{a}	0.241^{a}	0.242^{a}	0.236^{a}	0.237^{a}	0.232^{a}	0.240^{a}	0.236^{a}
	(0.055)	(0.056)	(0.058)	(0.057)	(0.055)	(0.056)	(0.053)	(0.057)	(0.055)
R^2	0.31	0.30	0.31	0.31	0.30	0.33	0.33	0.31	0.34
F-stat. on the instrument(s)	15.21	16.43	55.27	30.95	16.01	31.08	12.32	47.81	33.33

Note: 4,344 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; *a*, *b*, *c* denote significance at 1%, 5%, 10%; all regressions include CBSA and year fixed effects

Table 3: First-stage estimation of the relationships between the instruments and airport size.

The results in Table 3 demonstrate that the instruments explain a significant amount of the variation in airport size. The F-statistics are sufficiently large for each to be considered a relevant instrument for airport size.[17] The ‘aircraft model’, ‘aircraft class’, and ‘number of seats’ instruments all reflect the type of aircraft, so I prefer to use only one of these. I suspect that the ‘aircraft model’ instrument is relatively weak because it is a relatively narrow a classification of aircraft type.[18] The ‘number of seats’ instrument is also strong, but I prefer the ‘aircraft class’ instrument because the information contained in the engine-type classification makes it somewhat richer.

The analysis continues using the ‘airline’, ‘aircraft class’, and ‘distance’ instruments. These instruments are each clearly relevant and the three categorizations are conceptually diverse. Columns 6, 7, and 8 of Table 3 use pairs of the three selected instruments in the first-stage estimation and Column 9 uses all three. For each combination the F-statistic is reasonably large and the coefficients on the instruments are positive and generally significant, so it appears that

[17]Staiger and Stock (1997) established the customary threshold of 10 for the first-stage F-statistic. Stock and Yogo (2005) calculated critical values under the assumption of independent and identically distributed errors. With a maximal size of 15% – meaning that a Wald test of $\beta = \beta_0$ with a 5% confidence level rejects the null no more than 15% of the time – the critical values are 8.96 in the case of one instrument and one endogenous regressor and 12.83 when there are three instruments and one endogenous regressor. With a maximal size of 10% the critical values are 16.38 for one instrument and one endogenous regressor and 22.30 for three instruments and one endogenous regressor.

[18]By its nature the instrument is weak for sufficiently narrow or broad categories. The narrower the category, the fewer observations there are outside the CBSA to calculate the overall growth rate, and the more the traffic reflects idiosyncratic changes in other places rather than overall factors for the category. The broader the category, the closer the overall growth rate is to the aggregate growth in traffic for the entire US, which is captured by the year fixed effects.

all three instruments contribute to the variation explained by the model.

The results from the second stage of the TSLS estimation are presented in Table 4. Columns 1 through 4 use the number of flights as the measure of airport size: Columns 1 to 3 use each of the three preferred instruments and Column 4 uses all three in combination. Columns 5 to 7 use the alternative measures of airport size with all three types of instruments.

I run Kleinbergen-Paap *rk* Wald tests to evaluate the relevance of the instruments, Sargan-Hansen tests for the overidentifying restrictions in the regressions with more than one instrument, and Hausman tests to determine whether the OLS and TSLS coefficients are statistically different. In Table 4 and all TSLS results tables that follow, I report the F-statistics from the Kleinbergen-Paap *rk* Wald tests and the p-values from the Sargan-Hansen and Hausman tests.

Airport-size measure	(1) TSLS Flights	(2) TSLS Flights	(3) TSLS Flights	(4) TSLS Flights	(5) TSLS Seats	(6) TSLS Pass.	(7) TSLS Air access
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.030^a	0.044^b	0.034	0.036^a	0.045^a	0.046^a	0.026^b
	(0.010)	(0.018)	(0.022)	(0.012)	(0.016)	(0.016)	(0.010)
$\ln(A_{m,t})$	0.001	0.004	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
$\ln(emp_{m,t})$	-0.078^a	-0.082^a	-0.079^a	-0.080^a	-0.079^a	-0.077^a	-0.078^a
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)
First-stage statistic	15.21	55.27	16.01	33.33	24.31	20.17	26.12
Overid. p-value				0.59	0.24	0.60	0.42
Hausman test p-value	0.03	0.02	0.13	0.00	0.01	0.04	0.01
'Airline' instrument	Y			Y	Y	Y	Y
'Aircraft class' instrument		Y		Y	Y	Y	Y
'Distance' instrument			Y	Y	Y	Y	Y

Note: 4,344 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; *a*, *b*, *c* denote significance at 1%, 5%, 10%; all regressions include CBSA and year fixed effects

Table 4: Second-stage estimation of the effect of airport size on employment.

The TSLS coefficients on $\ln(A_{m,t+1}) - \ln(A_{m,t})$ in Table 4 indicate that airport size has a positive effect on employment. The magnitude of the effect varies somewhat with the choice of instrument but is around 0.03 to 0.04 when airport size is measured as the number of flights. The coefficients are slightly larger when airport size is measured as the number of seats or passengers and slightly smaller when the 'air access' measure is used, but each of the coefficients is reasonably close to 0.04. This figure is taken as the overall effect of airport size on employment, though interpretations can be made using the different measures where these are relevant to specific policy questions. The overidentification tests are not rejected in any of the regressions, so there is no evidence of the overidentifying restrictions being invalid.

The elasticity of 0.04 for the effect of airport size on employment can be expressed in terms of the number of jobs in a CBSA of a particular size. For example, 41.5% of the population of the sample CBSAs in 2015 were in employment, so a typical CBSA with one million residents would have around 415,000 people employed. An elasticity of 0.04 therefore implies that a 10% increase in the size of the local airport would increase local employment by around $10\% \times 0.04 \times 415,000 \simeq 1,660$.

If traffic at the local airports increases, the number of employees required to operate them will tend to increase, as additional cabin and ground crew are required. It is thus natural to ask what proportion of the jobs created in the CBSA are simply the additional workers required to operate the airport. Though relatively little data is available about local employment in the air travel industry, it is possible to generate rough estimates of the proportion of jobs created that are in air operations. The elasticity of 0.04 from Table 4 implies that a 1% increase in air traffic leads to a $1\% \times 0.04 = 0.04\%$ increase in overall local employment. According to data from the BTS, approximately 0.55% of total employment in US CBSAs in 2010 was in the air travel industry. If we assume – imperfectly but within the constraints of the available data – that employment in the air travel industry increases in proportion to air traffic, then a 1% increase in local air traffic would lead to an increase in local air-industry employment that is $1\% \times 0.55\% = 0.0055\%$ of overall local employment. The ratio of the change in overall employment to the change in air-industry employment is thus $0.04\%/0.0055\% \approx 7.3$, so for every local job created in the air travel industry there are roughly six jobs created in other industries in the CBSA.[19]

The TSLS coefficients on the change in airport size are larger in magnitude than the OLS coefficients and the Hausman tests indicate that in most cases the differences are significant. This deserves some explanation as it suggests negatively-biased OLS coefficients – the opposite of what one would expect if employment has a positive effect on airport size. However, this finding is common in studies that use instrumental variables to estimate the effects of transport infrastructure on economic outcomes. Duranton and Turner (2012) offer two potential explanations for this phenomenon: (1) a variable such as ‘amenities’ may be missing from the estimation and correlate negatively with infrastructure and (2) reverse causality whereby employment negatively affects infrastructure.

[19] Some of the jobs outside of the air travel industry may be located at the airport. This would include retail and restaurant workers, who are not involved in flight operations. As a result, the ratio of the change in total CBSA employment to the change in all employment at the airport would be somewhat smaller than 7.3.

The first of these explanations does not seem likely to apply here as amenities are largely time-invariant factors such as climate and coastal location and these will be captured in the CBSA fixed effects. The same would apply to any other time-invariant factors and any factors that applied to all locations at a given time would be captured by the year fixed effects. The second explanation is more plausible, as investments in airport infrastructure may be made in response to negative shocks to employment as a way of stimulating the economy. This would bias the OLS coefficient downwards.

It is plausible that airport size could affect employment through ticket prices, as more traffic may imply more competition between airlines or lower average costs due to economies of scale, either of which could lead to lower ticket prices. This possibility is explored in Appendix A5, but there is shown to be little correlation between ticket prices and either the instruments or employment growth.

4.1 Longer-term effects of changes in airport size

The results presented above use periods of one year for the changes in airport size and employment. The effects captured in the estimation thus accumulate over a period of no longer than one year. This section investigates whether the effects that accrue over longer periods of time are different. I do this first by adding lagged airport growth to the main results, which can be used to test whether changes in airport size have significant effects over periods of longer than one year and thus whether these lags should be included in the analysis. Secondly, I run a set of regressions with the growth in airport size and employment measured over longer periods of time. Appendix A6 repeats the estimation with future changes in airport size.

Table 5 presents the results from the OLS estimation of (10) with additional variables for lagged rates of airport growth. Column 1 is the main specification from Table 2, while Columns 2 to 7 each add the airport-growth variable for an additional lagged year. The controls for initial airport size and employment in each regression are the values at the beginning of the first period in the estimation.

Lagged years (s)	(1) OLS 0	(2) OLS 1	(3) OLS 2	(4) OLS 3	(5) OLS 4	(6) OLS 5	(7) OLS 6
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.011^a	0.009^a	0.008^a	0.008^a	0.009^a	0.010^a	0.010^a
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
$\ln(A_{m,t}) - \ln(A_{m,t-1})$		-0.000	-0.002	-0.003	-0.004	-0.005^c	-0.003
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$\ln(A_{m,t-1}) - \ln(A_{m,t-2})$			0.001	-0.000	0.000	0.000	-0.002
			(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
$\ln(A_{m,t-2}) - \ln(A_{m,t-3})$				-0.006^a	-0.007^a	-0.007^a	-0.008^a
				(0.002)	(0.002)	(0.002)	(0.002)
$\ln(A_{m,t-3}) - \ln(A_{m,t-4})$					-0.004	-0.003	-0.005
					(0.003)	(0.003)	(0.003)
$\ln(A_{m,t-4}) - \ln(A_{m,t-5})$						-0.006^b	-0.007^a
						(0.002)	(0.003)
$\ln(A_{m,t-5}) - \ln(A_{m,t-6})$							-0.004
							(0.003)
$\ln(A_{m,t-s})$	-0.003^c	-0.004^b	-0.005^a	-0.006^a	-0.005^a	-0.004^c	-0.005^b
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\ln(emp_{m,t-s})$	-0.074^a	-0.079^a	-0.078^a	-0.069^a	-0.061^a	-0.050^a	-0.041^a
	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.50	0.51	0.51	0.51	0.50	0.51	0.51
Number of observations	4,344	4,163	3,982	3,801	3,620	3,439	3,258

Note: 181 CBSAs for each regression; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table 5: OLS estimation with lagged rates of airport growth.

The results in Table 5 indicate that employment growth in the current year has a weak negative relationship with past growth in airport size. Some of the coefficients on past rates of airport growth are not significant while others are negative and significant. However, the coefficient on log airport growth from t to $t+1$ varies little with the inclusion of the variables for lagged airport growth.

Table 6 reproduces the main TSLS estimates with multiple lagged rates of airport growth. Columns 2 to 7 add additional lagged years of airport growth to the second-stage relationship (10) and the three chosen instruments for each of those lagged years.

Lagged years (s)	(1) TSLS 0	(2) TSLS 1	(3) TSLS 2	(4) TSLS 3	(5) TSLS 4	(6) TSLS 5	(7) TSLS 6
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.036^a	0.027^b	0.029^b	0.031^c	0.034^b	0.026^b	0.018^c
	(0.012)	(0.013)	(0.012)	(0.017)	(0.016)	(0.012)	(0.010)
$\ln(A_{m,t}) - \ln(A_{m,t-1})$		−0.004	−0.010	−0.011	−0.010	−0.001	0.016
		(0.007)	(0.009)	(0.012)	(0.016)	(0.013)	(0.012)
$\ln(A_{m,t-1}) - \ln(A_{m,t-2})$			0.002	−0.001	−0.004	−0.001	−0.015
			(0.007)	(0.008)	(0.009)	(0.010)	(0.013)
$\ln(A_{m,t-2}) - \ln(A_{m,t-3})$				−0.008	−0.004	−0.001	0.006
				(0.009)	(0.011)	(0.009)	(0.011)
$\ln(A_{m,t-3}) - \ln(A_{m,t-4})$					−0.009	−0.005	−0.010
					(0.009)	(0.009)	(0.010)
$\ln(A_{m,t-4}) - \ln(A_{m,t-5})$						−0.007	−0.005
						(0.008)	(0.009)
$\ln(A_{m,t-5}) - \ln(A_{m,t-6})$							0.010
							(0.007)
$\ln(A_{m,t-s})$	0.002	−0.001	−0.004	-0.004^c	-0.004^c	−0.002	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
$\ln(emp_{m,t-s})$	-0.080^a	-0.081^a	-0.078^a	-0.070^a	-0.061^a	-0.050^a	-0.045^a
	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
First-stage statistic	33.33	12.89	7.09	6.05	2.16	1.58	2.37
Overid. p-value	0.59	0.12	0.45	0.27	0.54	0.58	0.19
Hausman test p-value	0.00	0.15	0.19	0.23	0.06	0.16	0.05
Number of observations	4,344	4,163	3,982	3,801	3,620	3,439	3,258

Note: 181 CBSAs for each regression; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; instrumental variable categories: airline, aircraft class, and distance; all regressions include year and CBSA fixed effects

Table 6: TSLS estimation with lagged rates of airport growth.

The results in Table 6 indicate that changes in employment are driven by changes in airport size over the current year, but not by earlier changes in airport size. The F-statistics on the first stage are weaker when the lagged variables are added. However, the coefficient on airport growth over the current year changes only slightly with the inclusion of lagged rates of growth, while the coefficients on the lagged growth rates are not statistically different from zero.

Bartik (1991) recommends selecting the appropriate number of lagged explanatory variables based on minimizing the out-of-sample prediction error. This type of exercise is trivial in the context of the results presented in Table 6, as the lagged growth rates do not have significant coefficients and thus do not contribute substantially to the variation explained by the model.

To further study how the effects of a change in airport size may develop over time, I also estimate the system of equations (9) and (10) using growth in airport size and employment over periods of more than one year. The results are presented in Table 7, with the OLS results in Panel A and the TSLS results in Panel B. To ensure the independence of the observations, the intervals should not overlap. This means that the sample size decreases dramatically with the period length. However, for periods of longer than one year it is possible to construct separate samples starting in different years, which is done for periods of two and three years in Table 7 to check for robustness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Period length in years (s)	1	2	2	3	3	3	4	5
First year of the sample	1991	1991	1992	1991	1992	1993	1991	1991
Panel A. OLS estimation.								
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.011^a	0.016^a	0.016^a	0.028^a	0.022^a	0.018^a	0.030^a	0.016
	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
$\ln(A_{m,t})$	-0.003^c	-0.003	-0.006^c	-0.002	-0.004	-0.011^c	0.000	-0.022^c
	(0.001)	(0.003)	(0.004)	(0.005)	(0.007)	(0.006)	(0.009)	(0.012)
$\ln(emp_{m,t})$	-0.074^a	-0.153^a	-0.168^a	-0.235^a	-0.278^a	-0.248^a	-0.307^a	-0.460^a
	(0.008)	(0.017)	(0.018)	(0.024)	(0.026)	(0.028)	(0.030)	(0.036)
R^2	0.50	0.59	0.65	0.66	0.70	0.71	0.74	0.80
Panel B. TSLS estimation. Instrumental variable categories: airline, aircraft class, and distance.								
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.036^a	0.035^a	0.042^b	0.040^b	0.040	0.042^b	0.052^c	0.034
	(0.012)	(0.012)	(0.018)	(0.017)	(0.026)	(0.019)	(0.031)	(0.023)
$\ln(A_{m,t})$	0.002	0.005	0.004	0.004	0.007	0.004	0.016	-0.007
	(0.003)	(0.006)	(0.007)	(0.010)	(0.015)	(0.012)	(0.022)	(0.020)
$\ln(emp_{m,t})$	-0.080^a	-0.160^a	-0.178^a	-0.240^a	-0.287^a	-0.260^a	-0.317^a	-0.464^a
	(0.009)	(0.017)	(0.019)	(0.023)	(0.028)	(0.029)	(0.031)	(0.031)
First-stage statistic	33.33	17.35	9.05	11.42	8.51	10.38	6.23	4.74
Overid. p-value	0.59	0.19	0.83	0.98	0.64	0.68	0.94	0.19
Hausman test p-value	0.00	0.11	0.08	0.48	0.42	0.10	0.45	0.49
Number of observations	4,344	2,172	1,991	1,448	1,267	1,267	1,086	724

Note: 181 CBSAs for each regression; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table 7: OLS and TSLS estimation with growth in airport size and employment measured over periods of one to five years.

The OLS results in Table 7 indicate that changes in airport size are correlated with changes in local employment and GDP for most period lengths. The number of observations decreases as the period length increases, which may explain why the estimates are weaker for longer period lengths, but the coefficients on the change in airport size are positive and significant for all period lengths up to four years. The magnitudes of the coefficients suggest that the correlation may become stronger as the period length becomes longer.

The TSLS results in Table 7 do not exhibit any clear relationship between the length of the period and the magnitude of the effect on employment. The estimates for longer period lengths, having fewer observations, have larger standard errors on the coefficients and lower F-statistics in the first stage. However, the magnitude of the coefficient on the change in airport size is broadly consistent across the range of period lengths. This suggests that a given change in airport size has roughly the same effect on employment in the first year as it does over a period of several years.

The results from both the lagged growth in airport size and the various period lengths imply that the effect of airport size on employment accrues rapidly – mostly within one year. This finding supports the use of one-year periods in the estimation. It may also be surprising, as one might except the effects of infrastructure to take a long time to accrue. A possible explanation is that the type of variation explained by the instruments is largely from marginal changes in traffic at well-established airports. These effects may accrue mostly through the reallocation of local factors, which occurs quickly, whereas the effects of a major investment such as a brand new airport may only be fully realized when capital and workers are drawn from other places.

4.2 Alternative measures of economic growth

In this section I estimate the effects of airports on a range of other outcome variables that directly or indirectly reflect economic growth. Table 8 presents the results of the estimation for eight such variables: the number of firms, population size, the employment rate (the proportion of the population who are employed), aggregate payroll, mean wage, personal income per capita, estimated GDP, and the index of house prices. Each of these variables appears in log differences as the dependent variable in (10) and in log level as the control variable on the right-hand side. Panel A presents the OLS results and Panel B presents the TSLS results.

	(1) Number of firms	(2) Population	(3) Employ. rate	(4) Aggregate payroll	(5) Mean wage	(6) Pers. inc. per capita	(7) GDP	(8) House prices
Panel A. OLS estimation.								
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.007^a	0.005^a	0.006^a	0.009^b	-0.000	0.002	0.014^a	0.018^a
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.004)	(0.005)
$\ln(A_{m,t})$	-0.001	0.002^b	-0.006^a	-0.004^b	0.001	-0.004^c	-0.004	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
$\ln(outcome_{m,t})$	-0.047^a	-0.032^a	-0.125^a	-0.065^a	-0.150^a	-0.138^a	-0.054^a	-0.077^a
	(0.005)	(0.006)	(0.013)	(0.009)	(0.017)	(0.030)	(0.011)	(0.008)
R^2	0.63	0.59	0.49	0.47	0.26	0.34	0.38	0.51
Panel B. TSLS estimation. Instrumental variable categories: airline, aircraft class, and distance.								
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.015^a	0.009^a	0.026^b	0.042^b	0.009	0.019^b	0.040^a	0.019
	(0.005)	(0.003)	(0.011)	(0.016)	(0.008)	(0.009)	(0.010)	(0.014)
$\ln(A_{m,t})$	0.001	0.003^a	-0.002	0.003	0.003	-0.000	0.006^c	0.002
	(0.001)	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
$\ln(outcome_{m,t})$	-0.049^a	-0.033^a	-0.130^a	-0.072^a	-0.153^a	-0.141^a	-0.058^a	-0.077^a
	(0.005)	(0.005)	(0.013)	(0.010)	(0.016)	(0.031)	(0.011)	(0.008)
First-stage statistic	31.84	31.85	32.58	33.00	31.08	31.07	33.28	35.32
Overid. p-value	0.58	0.15	0.80	0.41	0.61	0.29	0.47	0.06
Hausman test p-value	0.04	0.17	0.01	0.01	0.19	0.01	0.00	0.38

Note: 4,344 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; *a*, *b*, *c* denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table 8: Relationships between airport size and various measures of economic growth.

The TSLS coefficients in Table 8 exhibit positive effects of the change in airport size on six of the eight outcome variables. The effect on the number of firms is positive but smaller than the effect on the number of employees. This suggests that an increase in the size of the airport leads to both new firms being created and existing firms hiring additional workers. There is also a positive effect on the population. Comparing the magnitudes of the coefficients for employment and population and considering the levels of these variables, the effect of airport size on the population in absolute terms is three-fifths as large as the absolute effect on employment.[20] However, this does not imply that three out of every five of the jobs created are taken up by migrants, as some of the migrants may be attracted by the amenity value of the airport or may be family members who accompany the workers.[21]

There is a positive effect of airport size on the employment rate, so an increase in airport size leads to a greater proportion of the population being employed. The effect on aggregate payroll is positive and similar in magnitude to the effect on employment. It is thus not surprising that the effect on the mean wage, which is measured as payroll divided by employment, is not statistically different from zero. Although there is no measured effect on mean wages, there is a positive effect on personal income per capita, which could be because of the positive effect on the proportion of the population who are employed.

The lack of an effect on wages deserves some explanation, as it may appear not to be consistent with a general increase in economic activity. One possible explanation is that the supply of labour may be so elastic, at least in the sectors where employment is affected by the airport, that an increase in the demand for labour does not cause an increase in wages. Another possible explanation is that airports have an amenity value, so increased air connections make it more desirable to live in the local area. This would imply that labour supply shifts out when the airport is expanded, which may happen to match the shift in labour demand and lead to a small net change in the equilibrium wage.

The effect of airport size on GDP is positive and similar in magnitude to the effect on employment. There is thus no evidence that airport size has any effect on output per worker. However, this does not imply that there is no effect on total factor productivity, as it could sim-

[20]The effect of the number of flights on employment has an elasticity of 0.036 whereas the effect on the population has an elasticity of 0.009. The relative numbers of individuals these elasticities represent can be illustrated using an example. The employment in the sample is around 41.5% of the total population, so a CBSA with one million residents would have around 415,000 residents on average. A 1% increase in the number of departing flights would therefore lead to an increase in employment of $1\% \times 0.036 \times 415,000 \simeq 149.4$ and an increase in the population of $1\% \times 0.009 \times 1,000,000 \simeq 90.0$. The increase in population is thus $90.0/149.4 \approx 0.602$ as large as the increase in employment.

[21]Studies of the effects of arbitrary increases in regional employment generally find that in the long run around a quarter of the new jobs created are attributable to increased employment for existing residents (Bartik, 1993).

ply be that the newly-hired workers are less productive that those who were already employed, or that capital does not increase in line with employment. The effect of airport size on house prices is not significantly different from zero, despite the positive effects on population and employment. This appears to suggest either that the size of the effect is too small to be measured, or that the supply of housing is reasonably elastic.

4.3 Industry-level employment

To give a deeper understanding of how airports affect local employment, Table 9 presents estimates of the effects of airport size on employment in particular industries. The OLS and TSLS results are presented in separate panels.

The official US industry classification changed during the period of the data, from the Standard Industrial Classification (SIC) to the North American Industry Classification System (NAICS). Furthermore, the employment data in the County Business Patterns have many suppressed values at lower levels of aggregation than two-digit industries. It is therefore necessary to use broad definitions of industries and to create a mapping between the SIC and NAICS codes. The industry groupings used are *construction*, *manufacturing*, *wholesale and retail trade*, *transport and utilities*, and *other services*. The mapping of these industries to the SIC and NAICS codes and summary statistics for the industries are detailed in Appendix A7. As there is a discrete change in how employment is defined between 1997 and 1998, the observations for growth rates that overlap this change are excluded from the estimation.

Industry	(1) Construc- tion	(2) Manufact- uring	(3) Wholesale & ret. trade	(4) Transport & utilities	(5) Other services
Panel A. OLS estimation.					
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.049^a	0.022^c	0.009^c	0.024^b	0.009^b
	(0.008)	(0.011)	(0.005)	(0.010)	(0.004)
$\ln(A_{m,t})$	-0.003	-0.013	-0.002	0.013^c	0.001
	(0.005)	(0.011)	(0.003)	(0.007)	(0.004)
$\ln(emp_{m,t})$	-0.164^a	-0.202^a	-0.040^a	-0.173^a	-0.090^a
	(0.010)	(0.051)	(0.005)	(0.013)	(0.011)
R^2	0.43	0.22	0.28	0.21	0.25
Panel B. TSLS estimation. Instrumental variable categories: airline, aircraft class, and distance.					
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.116^a	0.014	0.012	0.052	0.051^b
	(0.030)	(0.045)	(0.018)	(0.037)	(0.026)
$\ln(A_{m,t})$	0.010	-0.015	-0.001	0.018^c	0.009
	(0.008)	(0.014)	(0.004)	(0.010)	(0.006)
$\ln(emp_{m,t})$	-0.169^a	-0.202^a	-0.040^a	-0.174^a	-0.095^a
	(0.010)	(0.050)	(0.005)	(0.013)	(0.011)
First-stage statistic	34.43	32.49	32.89	33.09	30.17
Overid. p-value	0.24	0.42	0.58	0.26	0.17
Hausman test p-value	0.02	0.94	0.88	0.60	0.12

Note: 4,163 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table 9: Relationships between airport size and employment in specific industries.

The results in Table 9 indicate that the measured effect of airport size on employment is driven by changes in two of the five industries. This contrasts with the OLS results, which indicate at least weak correlation between airport size and employment in each of the industries. The TSLS estimates show positive effects on *construction* and on *other services*, but no measurable effects on employment in *manufacturing*, *wholesale and retail trade*, or *transport and utilities*. Though the coefficient for *construction* is larger than that for *other services*, the level of employment in services is roughly seven times that in *construction*, so these results suggest that the bulk of the effect on employment is due to increased employment in *other services*. The positive effect on services employment and the lack of an effect on manufacturing employment is also consistent with the findings of Brueckner (2003) and Sheard (2014).

Many of the services included in *other services* involve personal interactions and have output that can be transferred with the aid of these personal interactions. As discussed in Sheard (2014), these types of services are more likely to benefit from air travel. The effect on *construction* could be related to the infrastructure and housing required by the population increase, even though there is no clear effect of airports on house prices in Table 8, but also to the construction necessary to expand the airport and related infrastructure. The supply of labour in *other services* and *construction* may also be relatively elastic, which would partly explain why employment in those sectors responds more to changes in airport size and would fit with the explanation given above for the lack of an effect of airport size on wages.

Employment in *transport and utilities* may be expected to increase when air traffic increases, as this industry includes airport operations, but the effect on the industry as a whole is not significant. The other industries that are not affected – *manufacturing* and *wholesale and retail trade* – have less intuitive connection with air travel.

4.4 Proximity to the airport within the metropolitan area

This section tests whether the effect of airport size on employment depends on the proximity to the airport. As airport improvements may be made with the goal of increasing employment near the airport, it is useful to understand how the effects differ by neighbourhood.

The estimation is run by dividing up each CBSA into zones defined by proximity to the airport, then estimating the effects on employment within each of these zones. The first set of tests divides up each CBSA into locations that are within 2 miles or 5 miles of the airport or are beyond each of these distances. This captures the proximity to the airport but ignores the fact that some such areas include downtown business districts while others do not.[22] This could be an issue as much of the employment in services, a sector shown in Table 9 to be affected by the airport, is likely to be located in the downtown area. To address this problem, the second set of tests divides up each CBSA into segments centred on the downtown core and at angles relative to the direction from the downtown core to the airport. This approach is neutral to the size and concentration of the downtown area – it divides neighbourhoods a given distance from the downtown core into those that are relatively near and far from the airport. One set of zones is separated by an axis that passes through the centre of the downtown and is perpendicular to the direction to the airport; a second set of zones is divided along axes at 60° and 120° from the direction to the airport. Figure 3 illustrates how these zones are defined using the Minneapolis-Saint Paul-Bloomington, MN-WI CBSA as an example.

[22] 5 of the 168 downtowns are within 2 miles of the respective airport, whereas 62 of the 168 downtowns are within 5 miles of the respective airport.

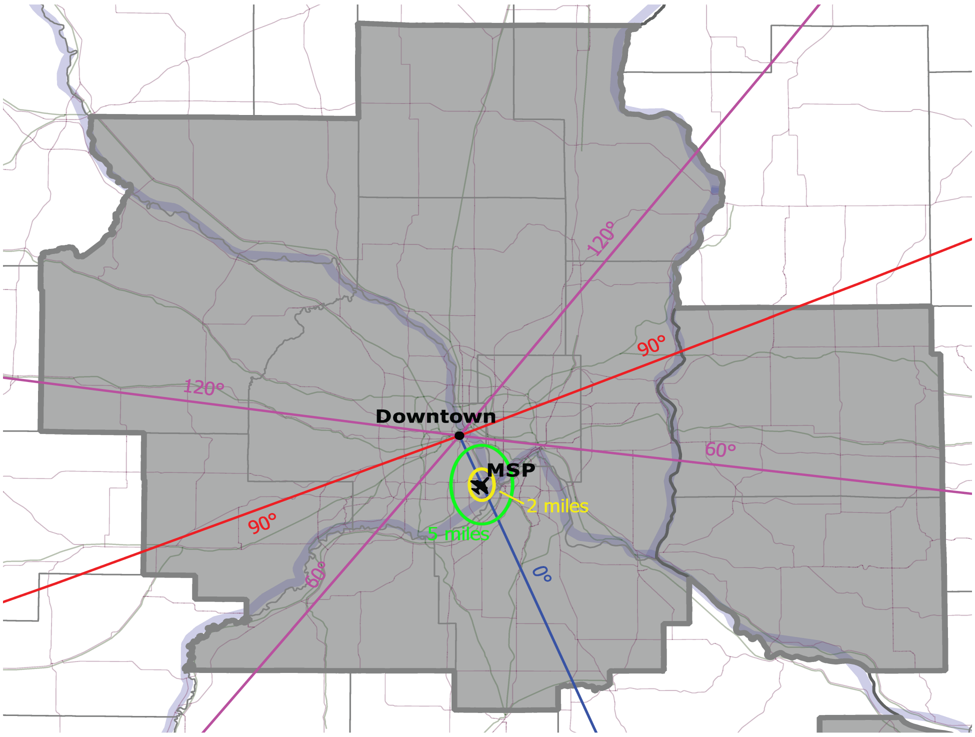

Figure 3: Map of the Minneapolis-Saint Paul-Bloomington, MN-WI CBSA showing the borders of the areas defined by the distance from and direction relative to the airport. This CBSA is served by Minneapolis-Saint Paul International Airport (MSP), the location of which is marked with the aircraft symbol. The two circles with radii of 2 miles and 5 miles are centred on the airport. The straight lines that emanate from the downtown of the CBSA mark axes at angles of 0°, 60°, 90°, and 120° – clockwise and anticlockwise – from the direction from the downtown to the airport.

The downtown of each CBSA is defined as the centre of the downtown employment cluster of the city specified as the 'core' of the CBSA.[23] It would be problematic to determine the appropriate direction to the airport in CBSAs with multiple commercial airports, so only the 168 CBSAs with a single airport in the main sample are used.[24] As this exercise requires employment data at a low degree of geographical aggregation, it uses the ZIP Code-level data from the County Business Patterns, which are available from 1994.[25]

[23]Lacking a reliable criterion for identifying the 'central business district' of a metropolitan area from data, the CBSA midpoints were chosen by hand. The primary source of information for this exercise was the maps and satellite photos on Google Maps. For each CBSA, the midpoint was chosen as the centre of the densest area of business activity – in most cases the tallest cluster of office buildings – in the 'core' of the CBSA. By definition the 'core' of a CBSA is its largest urban cluster, which is the first place listed in the name of the CBSA. For CBSAs with more than one urban cluster, the largest of these is used, rather than an intermediate location that may well be rural land or in a body of water.

[24]Denver-Aurora-Broomfield, CO and Austin-Round Rock-San Marcos, TX are also excluded as the main airports in these CBSAs changed locations during the period of the data.

[25]The ZIP Code-level employment data from the County Business Patterns are aggregated to the zones of the CBSAs using a two-step process. The first step uses the ZIP Code-level employment data to find the proportion of employment in each county that is located within each zone of the CBSA in a given year, where employment in ZIP Codes that cross the boundaries of a zone is allocated proportionally by area. The second step takes the county-level employment data from the County Business Patterns and assigns these to the zones according to the proportions from the first step.

The results of the estimation are presented in Table 10. The first column presents the baseline results with the employment data aggregated to the entire CBSA. Columns 2 to 5 divide the data at distances of 2 and 5 miles from the CBSA. Columns 6 and 7 split the data into locations within and beyond 90° of the direction from the downtown to the airport. Columns 8 to 10 divide the data into three zones, divided at 60° and 120° from the direction to the airport. The OLS results are presented in Panel A and the TSLS results are presented in Panel B.

Part of CBSA included	(1) All	(2) $\leq$ 2 miles	(3) $>$ 2 miles	(4) $\leq$ 5 miles	(5) $>$ 5 miles	(6) 0°-90°	(7) 90°-180°	(8) 0°-60°	(9) 60°-120°	(10) 120°-180°
Panel A. OLS estimation.										
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.009^a	0.025^b	0.018^a	0.015^a	0.009^a	0.013^a	0.012^b	0.016^a	0.009^b	0.017^b
	(0.003)	(0.012)	(0.006)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)
$\ln(A_{m,t})$	-0.004^b	0.000	0.001	−0.000	-0.004^b	0.000	−0.003	0.001	−0.003	−0.000
	(0.002)	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
$\ln(emp_{m,t})$	-0.081^a	-0.153^a	-0.153^a	-0.123^a	-0.081^a	-0.118^a	-0.105^a	-0.134^a	-0.134^a	-0.118^a
	(0.012)	(0.019)	(0.021)	(0.014)	(0.011)	(0.012)	(0.011)	(0.020)	(0.013)	(0.016)
R^2	0.50	0.22	0.24	0.33	0.50	0.37	0.38	0.29	0.38	0.29
Panel B. TSLS estimation. Instrumental variable categories: airline, aircraft class, and distance.										
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.026^b	0.026^b	0.049^c	0.025	0.038^a	0.030^b	0.011	0.034^b	−0.001	0.031
	(0.011)	(0.011)	(0.028)	(0.018)	(0.014)	(0.013)	(0.021)	(0.015)	(0.018)	(0.026)
$\ln(A_{m,t})$	−0.000	−0.000	0.006	0.002	0.005	0.004	−0.003	0.005	−0.006	0.003
	(0.003)	(0.003)	(0.008)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
$\ln(emp_{m,t})$	-0.087^a	-0.154^a	-0.153^a	-0.126^a	-0.087^a	-0.122^a	-0.105^a	-0.137^a	-0.133^a	-0.120^a
	(0.012)	(0.019)	(0.020)	(0.014)	(0.012)	(0.012)	(0.011)	(0.018)	(0.013)	(0.015)
First-stage statistic	11.45	11.09	11.20	11.44	11.47	11.24	11.33	11.11	11.42	11.15
Overid. p-value	0.96	0.54	0.36	0.31	0.96	0.21	0.84	0.15	0.94	0.36
Hausman test p-value	0.05	0.37	0.78	0.12	0.04	0.19	0.58	0.26	0.55	0.11

Note: 3,528 observations for each regression, representing 168 CBSAs; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table 10: Effects of airport size on employment within parts of each metropolitan area defined by their proximity to the respective airport. Columns 2 to 5 divide the locations by the distance from the airport. Columns 6 to 10 divide the locations by their direction from the downtown area relative to the direction from the downtown to the airport.

The results presented in Table 10 for employment by distance from the airport show no clear distinction between the different areas. The OLS estimates in Panel A exhibit a positive correlation for each of the zones, which is somewhat larger for nearer locations. The TSLS point estimates indicate a larger effect on employment at greater distances from the airport, though the coefficient for employment within 2 miles is more strongly significant than that for employment at more than 2 miles. One implication of these results is that the effect on employment is not limited to employment at the airport.

In contrast, the results for the direction relative to the airport exhibit two clear phenomena: changes in airport size (1) correlate positively with employment in all parts of a metropolitan area and (2) primarily affect employment in areas nearer the airport. The OLS coefficients on the change in airport size are positive, significant, and reasonably similar in magnitude for each CBSA segment, which is consistent with demand for air travel coming from throughout the CBSA. The TSLS coefficients on growth in airport size for the areas nearest the airport – between 0° and 90° and between 0° and 60° – are positive and significant, while the coefficients are not significant for the other areas. This suggests that, if we control for proximity to the downtown core, a change in airport size has a larger effect on employment in parts of the CBSA that are nearer the airport.

These results should allay some potential concerns about the validity of the instruments. Were the instruments capturing some variation in airport size that is correlated with employment but not due to the effect of the airport on employment, then a symptom could be that the measured effect applies over the same area that is represented in the OLS results. However, the OLS and TSLS coefficients in Table 10 exhibit different spatial patterns, with the former indicating a correlation between airport size and employment throughout the CBSA, whereas the latter indicate an effect on employment that is concentrated in parts of the CBSA nearer the airport.

5 Conclusion

This paper estimates the effects of changes in airport size on local employment and other economic outcomes. The topic is important for policy evaluation, as airport improvements are costly and normally conducted using public funds. Nevertheless, the existing evidence of the economic effects of airports is limited, due in part to the difficulties inherent in measuring the effects. This paper develops and applies a novel technique to measure the effects of airports that could be applied in future research.

The main finding is that airport size has a positive effect on local employment, with an elasticity of around 0.04. This implies that in a typical metropolitan area with a million residents, a 10% increase in local air traffic would increase local employment by around 1,660. In addition, for each job created in operating the airport, there are roughly six jobs created in other sectors of the local economy. The effect on employment appears to be concentrated in parts of the metropolitan area that are nearer the airport.

To further understand the effects of airports on the local economy, I estimate the effects of airports on a range of other variables including the number of firms, the local population, wages, the employment rate, and GDP. Airport size is found to have positive effects on the number of firms, population, and the employment rate, but not on wages. The effect of airport size on the population is smaller than the effect on employment, while the effect on the employment rate is also positive, which suggests that the jobs created by an airport improvement are taken up partly by migrants and partly by existing residents. The induced migration raises the question of how employment at the national level is affected, as the improvement of a given airport may have negative effects on employment in other places. This is a complex issue that is beyond the scope of the current paper but would represent a valuable topic for future research. There is also a positive effect on local GDP, with a magnitude similar to the effect on employment, so there is no evidence of output per worker being affected by airport size.

The estimates of the effects on employment by industry indicate that airport size has a positive effect on employment in the set of services that includes finance, consulting, and real estate but no measurable effect on manufacturing employment. These results are consistent with the finding of Sheard (2014) that airport size has a positive effect on the share of employment in tradable services but no effect on the share of employment in manufacturing. However, due to the limitations of interpreting effects on growth from cross-sectional variation in airport sizes, it was not clear in the previous paper whether the increase in services employment was due to an overall increase in local employment or simply a reallocation between local sectors. The results presented here suggest more clearly that services expand without displacing manufacturing activity. I also find that airport size has a positive effect on employment in construction, but no measurable effect on wholesale and retail trade or on transport and utilities.

The technique proposed in this paper would be straightforward to apply to further studies of the effects of airports. It could also be applied to other types of transport infrastructure such as roads, railways, and ports, as well as non-transport infrastructure such as electrical supply and communications networks. Two necessary conditions for applying the technique would be (1) that it is possible to quantify the infrastructure in terms of the level of traffic it carries and (2) that this traffic can be classified into categories that vary in prevalence depending on national- or regional-level factors.

The technique has three main advantages over alternative identification strategies. The first is the relative ease of obtaining the data required to apply it: as opposed to instruments that explain cross-sectional variation in current infrastructure, it does not require geographical or historical data that are often difficult to obtain or quantify. The second is that to apply the technique it is not necessary to identify a substantial change in policy or technology or some type of event such as a natural disaster or strike, which is not always possible. Indeed, as the variation is driven by overall changes in traffic by category, the method implicitly captures many such changes without it being necessary to identify them individually. The third is that, at least in the context of airports, the instruments explain a large amount of the variation in the level of infrastructure relative to the other techniques that have been applied. Another potential advantage of the technique is that it facilitates estimating the short-term effect of changes in infrastructure, whereas techniques that rely on cross-sectional variation are often better-suited to explaining long-term effects.

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A1 Categorizations used to construct the instruments

A1.1 Airlines

The categories used to construct the 'airline' instrument are the airlines listed in Table A1. The airlines are grouped according to the *Unique Carrier Code* assigned by the BTS, which tracks changes in airline codes over time and distinguishes different airlines that used the same code in different periods. Only airlines that had an average of at least 10 daily flights and 100 daily passengers in at least one year between 1991 and 2015 are included, though naturally the exclusion of these smaller airlines makes only a slight difference to the instrument.

Table A1 displays the numbers of flights and passengers for each airline. These are the aggregate amounts of traffic operated by the airline between 1991 and 2015 with an origin or destination in the contiguous United States. The list is presented in descending order of the number of flights operated.

Airline code	Airline name	Number of flights	Number of pass. ('000)	Airline code	Airline name	Number of flights	Number of pass. ('000)
WN	Southwest Airlines	22,356,265	2,099,953	EA	Eastern Air Lines	221,470	17,240
DL	Delta Air Lines	20,796,964	2,375,649	TB (1)	USAir Shuttle	219,841	15,263
AA	American Airlines	19,935,687	2,180,970	WS	Westjet	215,775	25,755
UA	United Air Lines	16,081,403	1,816,990	JM	Air Jamaica	213,511	24,669
US	US Airways	15,464,190	1,349,405	J7	Valujet Airlines	212,960	14,023
NW	Northwest Airlines	10,198,850	982,796	PA (1)	Pan American World Airways	198,026	22,288
MQ	American Eagle Airlines	9,269,027	289,693	C8 (1)	Chicago Express Airlines	185,095	3,879
CO	Continental Air Lines	9,205,140	919,262	HRZ	Allegheny Airlines	183,669	3,422
EV	Atlantic Southeast Airlines	7,248,543	258,537	CP (1)	Canadian Airlines	178,489	15,466
OO	SkyWest Airlines	7,110,892	263,790	ML (1)	Midway Airlines (Chicago, IL)	170,052	9,611
XE	ExpressJet Airlines	6,053,023	189,996	WST	West Isle Air	163,328	149
QX	Horizon Air	4,187,712	136,310	KL	KLM Royal Dutch Airlines	160,511	39,739
AS	Alaska Airlines	3,919,106	369,852	PT	Capital Cargo International	160,038	3,690
HP	America West Airlines	3,577,033	334,334	ZX	Air Georgian	157,333	1,542
YV	Mesa Airlines	3,544,184	132,434	NJ	Vanguard Airlines	147,636	11,046
TW	Trans World Airways	3,192,912	274,421	UP	Bahamasair	138,104	8,268
9E	Pinnacle Airlines	3,152,871	124,023	CM	Compania Panamena	136,593	13,050
OH	Comair	3,124,019	112,739	U2	UFS	136,516	4,207
FL	AirTran Airways Corporation	3,079,364	273,342	AV	Avianca	136,200	15,933
XJ	Mesaba Airlines	2,947,125	78,732	BF	MarkAir	127,673	6,736
ZW	Air Wisconsin	2,947,010	109,861	GQ	Big Sky Airlines	126,874	1,070
AX	Trans States Airlines	2,524,219	56,361	IB	Iberia	125,270	22,472
B6	JetBlue Airways	2,514,868	280,560	BW	Caribbean Airlines	113,060	12,403
RP	Chautauqua Airlines	2,121,262	71,788	KW	Carnival Air Lines	98,199	10,439
AC	Air Canada	1,565,753	118,758	U5	USA 3000 Airlines	95,257	11,900
HA	Hawaiian Airlines	1,548,935	160,732	CX	Cathay Pacific	94,643	24,132
9K	Cape Air	1,547,019	8,345	PD	Porter Airlines	91,864	3,596
17	Piedmont Airlines	1,465,350	35,033	3C	Regions Air	90,874	676
YX	Republic Airlines	1,358,127	81,031	1DQ	Island Airlines	75,929	499
OW	Executive Airlines	1,347,280	43,551	KP	Kiwi International	75,213	6,382
F9	Frontier Airlines	1,296,253	133,284	SR	Swissair Transport	71,366	13,737
16	PSA Airlines	1,249,632	47,535	RD	Ryan International Airlines	71,318	8,408
KH	Aloha Air Cargo	1,140,736	86,173	RG	Varig	71,009	11,605
S5	Shuttle America	1,039,937	48,870	GL	Miami Air International	70,563	5,248
9L	Colgan Air	956,816	19,419	KN	Morris Air Corporation	66,201	6,828
NK	Spirit Air Lines	911,420	112,104	5D	Aerolitoral	65,794	2,651
ZK	Great Lakes Airlines	872,834	6,562	N7	National Airlines	63,190	7,126
DH	Independence Air	769,234	22,789	L3	Lynx Aviation / Frontier Airlines	62,578	2,873
YX (1)	Midwest Airlines	729,720	40,580	MG	Champion Air	60,924	7,398
3M	Silver Airways / Gulfstream Int'l	707,444	8,263	JJ	Transportes Aeros Meridiona	60,283	11,070
QK	Air Canada Regional	677,153	21,175	W7	Western Pacific Airlines	58,319	4,503
TZ	ATA Airlines	657,717	87,927	Y4	Volaris	55,999	6,628
BA	British Airways	653,104	137,388	0JQ	Vision Airlines	52,374	2,242
OE	WestAir Airlines	651,950	7,994	WV (1)	Air South	50,628	3,087
HQ (1)	Business Express	620,932	7,627	LGQ	Lineas Aereas Allegro	45,114	5,187
MX	Mexicana	570,664	54,047	SLQ	Sky King	43,745	3,277
C5	CommutAir	522,081	9,560	0MQ	Air Choice One	43,165	171
AM	Aeromexico	481,740	42,341	FCQ	Falcon Air Express	41,749	3,422
G7	GoJet Airlines / United Express	473,684	24,700	RS	Sky Regional Airlines	41,658	2,300
KS	Peninsula Airways	467,353	3,291	EK	Emirates	41,186	11,102
CP	Compass Airlines	429,612	25,301	PCQ	Pace Airlines	40,579	2,849
ZV	Air Midwest	417,503	2,907	NA	North American Airlines	38,566	4,505
G4	Allegiant Air	403,600	54,563	T9	TransMeridian Airlines	38,443	4,772
LH	Lufthansa German Airlines	396,233	92,526	8N	Flagship Airlines	38,139	983
QQ	Reno Air	351,058	30,156	FF	Tower Air	30,985	10,936
VX	Virgin America	330,877	36,280	E9	Boston-Maine Airways	27,409	363
AF	Air France	300,964	66,820	W9	Eastwind Airlines	25,763	1,142
AL	Skyway Airlines	297,374	4,405	EM	Empire Airlines	25,737	425
JI (1)	Midway Airlines (Morrisville, NC)	295,780	14,887	P9	Pro Air	22,643	1,182
F8	Freedom Airlines	277,230	10,261	PN	Pan American Airways (1998–2004)	20,365	1,270
KAH	Kenmore Air Harbor	276,583	1,225	RV	Air Canada Rouge	19,900	2,651
JL	Japan Air Lines	265,414	66,590	JX	Southeast Airlines	12,677	1,313
K5	SeaPort Airlines	264,499	855	1AQ	Charter Air Transport	11,984	228
SY	Sun Country Airlines / MN Airlines	248,824	29,672	SX	Skybus Airlines	9,314	932
KE	Korean Air Lines	242,315	50,299	APN	Aspen Airways	6,981	314
YR	Grand Canyon Airlines	236,024	2,964	BE	Braniff International Airlines	6,832	667
TA	TACA International Airlines	232,765	23,915	A7 (1)	Air 21	5,935	217
VS	Virgin Atlantic Airways	224,556	65,096	ZA	Access Air	4,261	202

Note: the air traffic figures represent all flights originating or terminating in the contiguous US between 1 April 1990 and 31 March 2015; the numbers in parentheses in the airline codes are defined by the BTS to differentiate airlines that used the same code at different times

Table A1: List of airlines used to calculate the 'airline' instrument.

For time periods that overlap mergers and acquisitions, a common growth rate for all airlines involved is calculated based on the aggregate level of traffic for the combined entity. That is, if airline A acquires airline B and all subsequent traffic is coded for airline A, then the growth rate applied to both airlines for any period overlapping the merger is the traffic coded as airline A at the end of the period divided by the sum of the traffic for airlines A and B at the beginning of the period. The mergers and acquisitions this applies to are listed in Table A2. Other mergers between sizeable airlines in the data – where the traffic continues to be coded separately after the merger – are listed in Table A3.

Transition period	Airline retaining code and name		Airline made defunct	
1998-1999	FL	AirTran Airways Corporation	J7	Valujet Airlines
1999-2001	AA	American Airlines	QQ	Reno Air
2000-2002	AC	Air Canada	CP (1)	Canadian Airlines
2002-2003	AA	American Airlines	TW	Trans World Airways
2007-2009	US	US Airways	HP	America West Airlines
2009-2011	DL	Delta Air Lines	NW	Northwest Airlines
2011-2013	BW	Caribbean Airlines	JM	Air Jamaica
2011-2013	UA	United Air Lines	CO	Continental Air Lines

Table A2: List of mergers and acquisitions for which the subsequent traffic is classified with a single code.

Year of merger	Airline 1		Airline 2	
2005	OO	SkyWest Airlines	EV	Atlantic Southeast Airlines
2009	AV	Avianca	TA	TACA International Airlines
2010	WN	Southwest Airlines	FL	AirTran Airways Corporation
2013	AA	American Airlines	US	US Airways

Table A3: List of mergers and acquisitions for which the subsequent traffic is classified separately for the two pre-merger airlines.

A1.2 Aircraft models

The categories used to construct the ‘aircraft model’ instrument are the aircraft models listed in Table A4. The sample is limited to models that were used for an average of at least one daily flight and one daily passenger in at least one year between 1991 and 2015. Again the air traffic variables are the aggregates of all flights with an origin or destination in the contiguous US from 1991 to 2015. The aircraft models are listed in alphabetical order.

Index	Aircraft model	Number of flights	Number of pass. ('000)	Index	Aircraft model	Number of flights	Number of pass. ('000)
1	Arospatiale/Aeritalia ATR 42/72	3,772,762	120,927	50	Bombardier CRJ100/200	16,896,480	606,687
2	Arospatiale-BAC Concorde	25,207	1,322	51	Bombardier CRJ700/705/900	6,927,977	380,141
3	Airbus A300-100/200	201,089	31,246	52	British Aerospace BAe-146	1,304,075	60,142
4	Airbus A300-600	609,265	111,598	53	British Aerospace BAe-ATP	208,073	6,374
5	Airbus A310-200	41,742	5,654	54	British Aerospace Jetstream	1,871,152	20,972
6	Airbus A310-300	145,083	19,724	55	Cessna 172/180/182/185	77,444	76
7	Airbus A318	166,869	14,102	56	Cessna 205/206/207/209/210	1,971,207	3,137
8	Airbus A319	6,494,475	614,920	57	Cessna 208	1,711,747	6,771
9	Airbus A320-100/200	9,524,066	1,082,533	58	Cessna 402	1,594,880	7,558
10	Airbus A321	996,103	146,005	59	Cessna Citation II	2,409	17
11	Airbus A330-200	683,881	146,174	60	Cessna Citation X	4,578	15
12	Airbus A330-300	88,480	21,684	61	Convair CV-580	8,276	233
13	Airbus A340	30,224	5,705	62	De Havilland DHC2	437,665	1,041
14	Airbus A340-200	355,542	73,321	63	De Havilland DHC3	173,571	1,049
15	Airbus A340-300	80,289	16,406	64	De Havilland DHC6	499,950	5,583
16	Airbus A340-500	35,703	6,096	65	De Havilland DHC7	65,525	1,743
17	Airbus A340-600	88,421	21,989	66	De Havilland DHC8	6,494,588	196,218
18	Airbus A380-800	46,004	17,871	67	Dornier 228	23,930	331
19	Beechcraft Baron	12,188	17	68	Dornier 328	813,153	16,096
20	Beechcraft King Air	35,937	142	69	Embraer 110	97,083	630
21	Beechcraft Super King Air	4,236,633	34,529	70	Embraer 120	4,108,385	69,087
22	Boeing 707-100	4,734	350	71	Embraer 135/140/145	15,209,436	524,368
23	Boeing 707-300	6,335	651	72	Embraer 170/175	2,801,490	154,078
24	Boeing 717-200	3,098,155	267,656	73	Embraer 190	1,224,739	92,907
25	Boeing 727-100	398,243	26,095	74	Fairchild F-27	95,847	2,147
26	Boeing 727-200/231	9,614,565	875,769	75	Fairchild Swearingen Metroliner	791,807	7,204
27	Boeing 737-100/200	9,765,157	672,784	76	Fokker 70/100	2,518,773	150,147
28	Boeing 737-300	20,531,836	1,796,924	77	Fokker F28	823,209	33,446
29	Boeing 737-400	3,530,112	328,808	78	Grumman G-73 Mallard	12,775	141
30	Boeing 737-500	4,550,336	357,028	79	Gulfstream G150/G200/G450	4,357	12
31	Boeing 737-600	13,729	1,127	80	Gulfstream II/III/IV/V	5,404	21
32	Boeing 737-700	10,102,117	1,019,509	81	Ilyushin 62	10,565	875
33	Boeing 737-800	6,588,603	791,850	82	Ilyushin 96	3,127	340
34	Boeing 737-900	831,275	119,011	83	Lockheed L-1011	747,619	147,978
35	Boeing 747-100	331,772	95,569	84	McDonnell Douglas DC-8	46,617	5,444
36	Boeing 747-200/300	703,206	187,135	85	McDonnell Douglas DC-9	31,433,389	2,640,939
37	Boeing 747-400	1,667,976	457,257	86	McDonnell Douglas DC-10	1,469,915	284,541
38	Boeing 747-400F	9,447	30	87	McDonnell Douglas MD-11	301,936	55,920
39	Boeing 747-8	5,273	1,710	88	McDonnell Douglas MD-90	704,976	81,784
40	Boeing 747C	52,280	10,621	89	Nihon YS-11	5,127	72
41	Boeing 747SP	40,931	6,972	90	Pilatus Britten-Norman BN2/A	208,798	896
42	Boeing 757-200	12,615,232	1,706,357	91	Pilatus PC-12	109,721	435
43	Boeing 757-300	483,259	90,953	92	Piper PA-18/23/28/31/32/34/39	1,322,244	3,246
44	Boeing 767-200	1,452,182	194,922	93	Piper PA-30/31T	24,615	63
45	Boeing 767-300	3,526,842	600,747	94	Quest Kodiak 100	1,724	11
46	Boeing 767-400	374,869	78,246	95	Raytheon Beechcraft Hawker	2,091	5
47	Boeing 777-200/233	1,645,085	345,709	96	Saab 340	5,363,697	97,665
48	Boeing 777-300/333	142,609	35,662	97	Shorts 330/360	304,137	4,995
49	Boeing 787-800	31,384	5,592				

Note: the air traffic figures represent all flights originating or terminating in the contiguous US between 1 April 1990 and 31 March 2015

Table A4: List of aircraft models used to calculate the 'aircraft model' instrument.

A1.3 Aircraft classes

The categories used to construct the 'aircraft class' instrument are listed in Table A5. These are based on the *Aircraft Type Group* variable specified in the BTS data. To give a finer classification of aircraft size, the groups for the three types of jet aircraft are broken down by the number of seats in each aircraft.

Index	Aircraft class	Number of flights	Number of pass. ('000)
0	Piston, 1-Engine / Combined Piston / Turbine	3,299,509	6,523
1	Piston, 2-Engine	2,575,530	10,877
2	Piston, 3-Engine / 4-Engine	2,739	0
3	Helicopter / STOL	24,361	48
4	Turbo-Prop, 1-Engine / 2-Engine	30,427,669	584,792
5	Turbo-Prop, 4-Engine	83,776	2,119
6.1	Jet, 2-Engine, 1-99 seats	48,564,681	2,033,402
6.2	Jet, 2-Engine, 100-149 seats	87,870,258	7,628,860
6.3	Jet, 2-Engine, 150-199 seats	32,712,437	4,122,463
6.4	Jet, 2-Engine, 200+ seats	7,972,668	1,493,133
7.1	Jet, 3-Engine, 1-99 seats	19,543	488
7.2	Jet, 3-Engine, 100-149 seats	9,998,032	901,465
7.3	Jet, 3-Engine, 150-199 seats	2,371	73
7.4	Jet, 3-Engine, 200+ seats	2,516,986	488,376
8.1	Jet, 4-Engine / 6-Engine, 1-99 seats	1,313,764	60,175
8.2	Jet, 4-Engine / 6-Engine, 100-199 seats	55,820	3,902
8.3	Jet, 4-Engine / 6-Engine, 200-299 seats	585,464	113,872
8.4	Jet, 4-Engine / 6-Engine, 300-399 seats	2,519,468	678,925
8.5	Jet, 4-Engine / 6-Engine, 400+ seats	377,776	113,440

Note: the air traffic figures represent all flights originating or terminating in the contiguous US between 1 April 1990 and 31 March 2015

Table A5: List of aircraft classes used to calculate the 'aircraft class' instrument.

A1.4 Number of seats in the aircraft

The 'number of seats' instrument is constructed using the set of ranges of the number of seats in each individual aircraft in Table A6. The BTS T-100 data show the aggregate traffic by combination of route, airline, aircraft type, and month rather than details for the individual flights. The number of seats may vary for the same type of aircraft depending on what seat arrangement the airline chooses, so it is not possible to infer the number of seats directly from the type of aircraft. Instead, the numbers of seats are calculated as the mean number of seats per flight segment for each type of aircraft. All aircraft types in the data have a mean of fewer than 500 seats per flight segment, so no aircraft fall outside of the ten categories in Table A6.

	Number of seats		Number of	Number of
Index	Minimum	Maximum	flights	pass. ('000)
1	1	4	160,549	145
2	5	9	7,628,199	24,100
3	10	24	7,122,543	61,622
4	25	49	50,159,620	1,491,824
5	50	99	21,240,661	1,120,735
6	100	149	97,900,060	8,532,073
7	150	199	32,738,858	4,124,689
8	200	299	10,902,044	2,053,980
9	300	399	2,662,078	714,587
10	400	499	408,240	119,177

Note: the air traffic figures represent all flights originating or terminating in the contiguous US between 1 April 1990 and 31 March 2015

Table A6: List of ranges of numbers of seats used to calculate the 'number of seats' instrument.

A1.5 Distance flown

The 'distance' instrument is constructed using the set of ranges of distance flown in miles presented in Table A7. These distances are given in the BTS T-100 data. A handful of flight segments in the data are longer than 10,000 miles and these are simply excluded.

	Distance (miles)		Number of	Number of
Index	Minimum	Maximum	flights	pass. ('000)
1	0	125	21,447,207	523,936
2	125	250	36,272,684	1,754,292
3	250	375	35,631,863	2,173,077
4	375	500	23,437,425	1,594,297
5	500	625	19,957,035	1,531,882
6	625	750	15,967,930	1,273,578
7	750	875	13,088,044	1,134,274
8	875	1,000	11,638,680	1,133,397
9	1,000	1,250	16,599,916	1,729,470
10	1,250	1,500	7,721,769	862,212
11	1,500	1,750	8,181,865	1,028,962
12	1,750	2,000	3,792,694	491,369
13	2,000	2,500	5,874,551	790,652
14	2,500	3,000	2,178,468	336,281
15	3,000	3,500	1,085,064	201,859
16	3,500	4,000	2,136,030	422,481
17	4,000	4,500	1,908,798	390,194
18	4,500	5,000	1,032,922	198,178
19	5,000	6,000	1,538,114	360,791
20	6,000	7,000	873,659	214,318
21	7,000	8,000	309,468	79,157
22	8,000	9,000	73,747	16,125
23	9,000	10,000	6,869	656

Note: the air traffic figures represent all flights originating or terminating in the contiguous US between 1 April 1990 and 31 March 2015

Table A7: List of distance ranges used to calculate the 'distance' instrument.

A2 Fixed effects and controls in the TSLS estimation

Table A8 presents the results for the TSLS estimation of (9) and (10) with different selections of fixed effects and controls. Column 1 has no fixed effects and no controls for the initial number of flights or employment. Columns 2 through 4 add the year and CBSA fixed effects. Columns 5 through 7 add the controls for initial levels of air traffic and employment.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. First-stage estimation.							
$\ln\left(\hat{A}_{m,t+1}\right)-\ln\left(A_{m,t}\right)$	0.151^{a}	0.154^{a}	0.156^{a}	0.157^{a}	0.160^{a}	0.157^{a}	0.159^{a}
(‘airline’ instrument)	(0.040)	(0.042)	(0.041)	(0.044)	(0.042)	(0.043)	(0.041)
$\ln\left(\hat{A}_{m,t+1}\right)-\ln\left(A_{m,t}\right)$	0.177^{a}	0.187^{b}	0.166^{b}	0.185^{b}	0.324^{a}	0.184^{b}	0.329^{a}
(‘aircraft class’ instrument)	(0.063)	(0.074)	(0.066)	(0.078)	(0.063)	(0.078)	(0.062)
$\ln\left(\hat{A}_{m,t+1}\right)-\ln\left(A_{m,t}\right)$	0.812^{a}	0.822^{a}	0.657^{a}	0.597^{b}	0.359	0.599^{b}	0.355
(‘distance’ instrument)	(0.124)	(0.147)	(0.173)	(0.285)	(0.249)	(0.285)	(0.250)
$\ln\left(A_{m,t}\right)$					-0.205^{a}		-0.214^{a}
					(0.021)		(0.022)
$\ln\left(emp_{m,t}\right)$						0.102^{a}	0.236^{a}
						(0.033)	(0.055)
R^2	0.21	0.22	0.22	0.23	0.33	0.24	0.34
Panel B. Second-stage estimation. Instrumental variable categories: airline, aircraft class, and distance.							
$\ln\left(A_{m,t+1}\right)-\ln\left(A_{m,t}\right)$	0.078^{a}	0.091^{a}	0.024^{b}	0.034^{a}	0.036^{a}	0.034^{a}	0.036^{a}
	(0.012)	(0.012)	(0.010)	(0.013)	(0.012)	(0.012)	(0.012)
$\ln\left(A_{m,t}\right)$					-0.000		0.002
					(0.002)		(0.003)
$\ln\left(emp_{m,t}\right)$						-0.078^{a}	-0.080^{a}
						(0.008)	(0.009)
First-stage statistic	121.07	96.74	40.89	19.37	31.26	19.55	33.33
Overid. p-value	0.06	0.02	0.76	0.49	0.44	0.51	0.59
Hausman test p-value	0.00	0.00	0.06	0.01	0.00	0.01	0.00
CBSA fixed effects		Y		Y	Y	Y	Y
Year fixed effects			Y	Y	Y	Y	Y

Note: 4,344 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size

Table A8: TSLS results with and without the year and CBSA fixed effects and the controls for the initial levels of airport size and employment.

The results in Table A8 suggest that the inclusion of year and CBSA fixed effects are important for the estimation, but that the initial number of flights and employment controls make little difference. Without the fixed effects the instruments are far stronger, suggesting idiosyncratic differences between years and CBSAs. In particular, not including the year fixed effects leads to far stronger instruments and a larger coefficient in the second stage. This is likely due to trends in the US economy over time that affect both the instruments (by affecting overall air traffic) and employment. The presence of such trends makes the year fixed effects necessary. Not including the CBSA fixed effects also leads to stronger instruments but somewhat smaller coefficients in the second stage. The controls for initial air traffic and employment make only minor differences to the estimates in the first and the second stage.

A3 Calculating the instruments using fixed category shares

A potential concern about the instruments is that the share for each category is calculated at the beginning of each period and that these shares may change in some way that correlates with economic growth. To address this concern, Table A9 reproduces the main estimates for the effect of airport size on employment using two alternative sets of category shares in the calculation of the instruments. The first is the shares at the respective airports in 1991 and the second is the shares of the aggregate traffic from 1991 to 2015.

Naturally, neither the category shares in 1991 nor the shares over all year from 1991 to 2015 can change over the period of the data. Therefore, any overall relationship between the category shares and employment growth should be captured by the CBSA-level fixed effects. Taking the airlines as an example, if the shares of some airline in 1991 correlate with the annual rate of employment growth from 1991 to 2015, then this would be captured by the CBSA-level fixed effects.

A concern persists that the shares of a particular airline in 1991 may correlate with employment growth in some subset of the period, if that airline also had an unusually high or low rate of overall growth over the same period. This could be the case for the years immediately following 1991, but (1) using the 1991 shares should at least partially mitigate the concerns about using shares that are updated each year and (2) it was not possible to obtain data that could have been used to calculate category shares for any earlier period. This concern is naturally greater with the shares for all years from 1991 to 2015, but again not as great as with the constantly-updating shares used in the main results.

Base year for the instruments	(1) 1991	(2) 1991	(3) 1991	(4) 1991	(5) All yrs	(6) All yrs	(7) All yrs	(8) All yrs
Panel A. First-stage estimation.								
$\ln(\hat{A}_{m,t+1}) - \ln(A_{m,t})$ ('airline' instrument)	0.440^a (0.100)			0.291^a (0.073)	0.163^a (0.041)			0.107^a (0.024)
$\ln(\hat{A}_{m,t+1}) - \ln(A_{m,t})$ ('aircraft class' instrument)		0.053 (0.049)		0.011 (0.020)		0.436^a (0.093)		0.194^a (0.053)
$\ln(\hat{A}_{m,t+1}) - \ln(A_{m,t})$ ('distance' instrument)			0.957^a (0.153)	0.710^a (0.133)			1.051^a (0.149)	0.740^a (0.155)
$\ln(A_{m,t})$	-0.042^a (0.010)	-0.039^a (0.009)	-0.042^a (0.009)	-0.044^a (0.011)	-0.037^a (0.008)	-0.037^a (0.008)	-0.042^a (0.009)	-0.041^a (0.009)
$\ln(emp_{m,t})$	0.046^a (0.010)	0.043^a (0.009)	0.043^a (0.009)	0.047^a (0.011)	0.039^a (0.008)	0.042^a (0.008)	0.044^a (0.009)	0.043^a (0.009)
R^2	0.19	0.16	0.21	0.21	0.18	0.19	0.21	0.23
Panel B. Second-stage estimation. Instrumental variable categories: airline, aircraft class, and distance.								
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.034^a (0.011)	0.069 (0.083)	0.041 (0.029)	0.036^b (0.015)	0.071^a (0.021)	0.035^c (0.018)	0.030 (0.022)	0.043^b (0.018)
$\ln(A_{m,t})$	0.002 (0.003)	0.009 (0.017)	0.004 (0.006)	0.003 (0.003)	0.010^b (0.004)	0.002 (0.004)	0.001 (0.004)	0.004 (0.004)
$\ln(emp_{m,t})$	-0.079^a (0.009)	-0.087^a (0.022)	-0.081^a (0.011)	-0.080^a (0.009)	-0.088^a (0.010)	-0.079^a (0.009)	-0.078^a (0.010)	-0.081^a (0.009)
First-stage statistic	20.51	0.92	11.43	8.28	14.45	22.00	15.89	13.50
Overid. p-value				0.83				0.18
Hausman test p-value	0.02	0.30	0.10	0.01	0.00	0.15	0.23	0.00
Number of observations	4,286	4,344	4,344	4,286	4,344	4,344	4,344	4,344

Note: 181 CBSAs for each regression; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include CBSA and year fixed effects

Table A9: TSLS results for the effect of the number of flights on employment using the shares in 1991 and the shares of all traffic from 1991 to 2015 in the calculation of the instruments.

The coefficients in Table A9 are consistent with the main results in Table 4, which suggests that the main results are not simply an artefact of the shares used in the instruments being updated each year. In addition, the F-statistics for the instruments in Table A9 are reasonably large, with the exception of the instrument constructed using the shares of aircraft classes in 1991.

The coefficients on the change in airport size in Table A9 are broadly consistent in magnitude with the main results, though the standard errors are relatively high and thus not all of the coefficients are significant. The higher standard errors are partly explained by airlines and aircraft types ceasing to operate and being replaced by new airlines and models over time. This means that the instruments for later years are based on less information, as the airports host progressively more airlines or aircraft types that had not been in operation in 1991, and this even leads to some missing observations for the 'airline' instrument. Nevertheless, the results are broadly consistent with the main results.

A4 Robustness checks

This appendix tests the robustness of the main results presented in Tables 2 and 4 of the paper to a number of alternative sample selections, control variables, and geographical definitions. The first set of robustness checks tests the implications of various alternative sample selections, the results of which are presented in Table A10.

The first robustness checks in Table A10 test whether the results are sensitive to the size threshold for the metropolitan areas. In Column 1 the sample is limited to metropolitan statistical areas (MSAs): the CBSAs with at least 100,000 inhabitants in 2009. Column 2 uses the CBSAs with at most one million inhabitants in 2010. The coefficients on the change in airport size are similar to the main results.

Sample criterion	(1) MSA	(2) Pop. ≤1m	(3) ≥ 10,000 pass.	(4) ≥ 100 flights	(5) Non-cap. constr.	(6) Year ≤ 2007	(7) No larger near apt.	(8) Dist. instr. excl. CD	(9) 1990 MSAs	(10) 50-mile circles
Panel A. OLS estimation.										
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.010^a	0.009^a	0.013^a	0.011^a	0.010^a	0.009^a	0.011^a	0.011	0.010^a	0.010
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
$\ln(A_{m,t})$	-0.003^b	-0.003^c	−0.002	-0.002^c	-0.003^b	-0.004^b	-0.003^c	-0.003^c	−0.003	-0.003^b
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
$\ln(emp_{m,t})$	-0.070^a	-0.075^a	-0.076^a	-0.075^a	-0.072^a	-0.072^a	-0.074^a	-0.074^a	-0.075^a	-0.068^a
	(0.009)	(0.012)	(0.009)	(0.008)	(0.009)	(0.013)	(0.008)	(0.008)	(0.014)	(0.007)
R^2	0.51	0.45	0.50	0.50	0.48	0.38	0.50	0.50	0.48	0.58
Panel B. TSLS estimation. Instrumental variable categories: airline, aircraft class, and distance.										
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.034^a	0.030^b	0.035^a	0.036^a	0.028^a	0.033^a	0.036^a	0.037^a	0.021^b	0.036^a
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.012)	(0.012)	(0.011)	(0.010)	(0.008)
$\ln(A_{m,t})$	0.002	0.002	0.002	0.003	0.001	0.003	0.002	0.003	−0.000	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
$\ln(emp_{m,t})$	-0.076^a	-0.081^a	-0.081^a	-0.081^a	-0.076^a	-0.078^a	-0.080^a	-0.080^a	-0.077^a	-0.074^a
	(0.010)	(0.012)	(0.009)	(0.009)	(0.009)	(0.014)	(0.009)	(0.009)	(0.014)	(0.007)
First-stage statistic	28.94	16.53	37.20	33.39	43.38	24.59	33.33	41.99	24.78	24.85
Overid. p-value	0.92	0.61	0.44	0.45	0.36	0.53	0.59	0.66	0.80	0.01
Hausman test p-value	0.00	0.01	0.01	0.00	0.02	0.01	0.00	0.00	0.17	0.00
Number of observations	4,008	3,120	4,224	4,392	3,984	2,896	4,344	4,344	3,720	4,752
Number of metro areas	167	130	176	183	166	181	181	181	155	198

Note: robust standard errors clustered by metropolitan area in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table A10: Results from robustness tests run using alternative sample selection criteria.

Columns 3 and 4 apply a pair of alternative traffic thresholds for the airports: a minimum of 10,000 departing passengers in each year (the threshold for a *Primary Airport* according to the FAA definitions) and a minimum of 100 departing flights in each year. As the variation explained by the instruments may be less likely to be reflected in changes in actual traffic at airports that are already close to full capacity, Column 5 excludes all airports that were capacity constrained in 2014 according to the FAA (2015). The coefficient on airport size barely changes when these restrictions are applied, indicating that the results are not sensitive to the choice of airport-size threshold or the exclusion of capacity-constrained airports.

The Global Financial Crisis that occurred around 2008 was an unusual period for the US economy. To check whether the results are driven by the events of this period, Column 6 limits the sample to the period from 1991 to 2007. The coefficient on airport size does not change, suggesting that the results are not an artefact of the Crisis.

As travelling by air can be costly and the availability of flights varies between airports, individuals may travel from airports in neighbouring communities. To minimize the possibility of the estimates reflecting changes at nearby airports that are beyond the CBSA boundaries, Column 7 uses a sample that excludes any CBSA that borders a CBSA with a higher-category airport in 2010 according to the FAA classification of airports into Large Hub, Medium Hub, Small Hub, Nonhub Primary, Nonprimary Commercial Service, and Reliever. This restriction decreases the sample size by around one third and increases the strength of the instruments but the OLS and TSLS coefficients remain practically unchanged, so the results are robust to the presence of large airports in nearby areas.

With the 'distance' instrument there is a concern about approximate distances being correlated with the region a flight operates in. For example, Los Angeles and San Francisco are similar distances from the East Coast cities and there is a lot of traffic on these routes, so flights to San Francisco are heavily represented in the instrument for flights to Los Angeles. If California experiences positive growth, then the exclusion restriction could be violated. Column 8 excludes all flights with an endpoint in the same census division in the calculation of the overall growth rates for the 'distance' instrument. This makes no change to the coefficient on the change in air traffic while in fact the first-stage statistic becomes somewhat larger.

The final two robustness checks addressed in Table A10 concern the geographical aggregation of the data. To be defined as a CBSA in 2009, an area must have had a population of at least 10,000 in that year. A potential concern is that among the metropolitan areas near the threshold earlier in the period, only those with positive growth in recent years are included, which could bias the sample. To address this concern, Column 9 reproduces the estimates with the data aggregated to Metropolitan Areas (MAs) using the June 1990 definitions. The coefficient on the growth in airport size is somewhat smaller, but still strongly significant.

A further issue with the CBSA definitions is that they are collections of counties. Counties are much larger in the Western US than in the rest of the country, so CBSAs in California tend to capture more hinterland than CBSAs in the Northeast. Furthermore, nearby urban cores are more likely to be grouped into a single CBSA in the West. To correct for any potential bias this may cause, Column 10 applies a neutral geographical definition that is defined as locations within a circle of 50-mile radius around each airport that satisfies the 2,500-passenger minimum, but no nearer to any other such airport. The results using this definition are nearly identical to those obtained with the data aggregated by CBSA.

Table A11 applies a number of additional controls in the estimation. A potential concern is that the measured effect of airport size on employment could be partly driven by regional-level changes in employment levels that somehow correlate with the instruments. To address this concern, Columns 1 to 4 of Table A11 use year-by-census-division and year-by-state fixed effects in place of the year fixed effects in the standard specification. Though the fixed effects absorb some of the variation in the first stage, the coefficient on the change in air traffic is not substantially different when they are used.

Columns 5 to 10 of Table A11 add controls for CBSA-level time trends. Columns 5 and 6 include a linear time trend for each CBSA.[26] Columns 7 and 8 control for linear and square time trends for each CBSA, while Columns 9 and 10 include a third power. The strength of the instruments is reduced with the inclusion of the additional time trends, as these absorb some of the variation, but the TSLS coefficients remain significant and similar in magnitude to the main results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Year-by-census-div. fixed effects		Year-by-state fixed effects		Year variable for each CBSA		Year and year^2 for each CBSA		Year, year^2, year^3 for each CBSA	
	OLS	TSLS	OLS	TSLS	OLS	TSLS	OLS	TSLS	OLS	TSLS
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.011^a	0.034^a	0.010^a	0.024^b	0.011^a	0.037^a	0.011^a	0.046^a	0.009^a	0.036^b
	(0.003)	(0.012)	(0.003)	(0.010)	(0.003)	(0.012)	(0.003)	(0.015)	(0.003)	(0.015)
$\ln(A_{m,t})$	-0.000	0.004^c	0.001	0.004^c	-0.001	0.009^c	0.002	0.017^a	-0.000	0.016^c
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.006)	(0.003)	(0.009)
$\ln(emp_{m,t})$	-0.082^a	-0.088^a	-0.092^a	-0.095^a	-0.236^a	-0.250^a	-0.355^a	-0.380^a	-0.444^a	-0.462^a
	(0.010)	(0.011)	(0.010)	(0.010)	(0.018)	(0.020)	(0.017)	(0.020)	(0.024)	(0.024)
R^2	0.55		0.64		0.56		0.61		0.66	
First-stage statistic		34.16		31.58		23.79		10.12		6.89
Overid. p-value		0.09		0.01		0.46		0.25		0.41
Hausman test p-value		0.05		0.20		0.01		0.00		0.01

Note: 4,344 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; *a*, *b*, *c* denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include CBSA fixed effects and Columns 5-10 include year fixed effects

Table A11: Results from robustness tests that use year-by-region fixed effects and separate time trends for each CBSA.

[26] As the specification is in first differences, this corresponds to a square time trend in levels.

A5 Ticket prices

Increased traffic at an airport can be related to increased competition, which may imply lower ticket prices. If the measured effect of airport size on local employment is actually due to the change in prices rather than increased traffic, then the interpretation would be somewhat different. To test whether the results reflect the effect of ticket prices, Table A12 reproduces the main results using the instruments based on the number of flights and employment growth as the outcome variable, but ticket prices in place of airport size as the endogenous regressor. The analysis uses the DB1B ticket data from the BTS, which includes information about ticket prices from January 1993 onwards.

Two broad measures of ticket prices are used in Table A12: Columns 1 to 6 use the mean fare per ticket that originates or terminates at the airport and Columns 7 to 9 use the mean fare per mile of those tickets. These prices are calculated first using all tickets, then using a 'balanced' set of only the routes served in years t and $t+1$, and then only the ten busiest routes in terms of traffic.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ticket-price measure	Mean fare per ticket						Mean fare per mile		
Routes	All	All	All	All	Balanced	Top 10	All	Balanced	Top 10
Panel A. First-stage estimation.									
$\ln(\hat{A}_{m,t+1}) - \ln(A_{m,t})$ ('airline' instrument)	-0.000			-0.000	0.005	-0.001	0.004	0.003	-0.002
	(0.006)			(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)
$\ln(\hat{A}_{m,t+1}) - \ln(A_{m,t})$ ('aircraft class' instrument)		-0.037^c		-0.061^b	-0.062^a	-0.085^a	-0.031	-0.059^a	-0.082^a
		(0.021)		(0.024)	(0.021)	(0.026)	(0.021)	(0.021)	(0.025)
$\ln(\hat{A}_{m,t+1}) - \ln(A_{m,t})$ ('distance' instrument)			0.003	0.073	0.068	0.110^b	0.023	0.076	0.125^b
			(0.045)	(0.053)	(0.047)	(0.056)	(0.052)	(0.046)	(0.054)
$\ln(price_{m,t})$	-0.211^a	-0.211^a	-0.211^a	-0.210^a	-0.171^a	-0.245^a	0.004	0.003	-0.002
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.020)	(0.005)	(0.006)	(0.007)
$\ln(emp_{m,t})$	0.027	0.028	0.027	0.028	0.019	0.030	0.035^c	0.032^c	0.041^c
	(0.022)	(0.022)	(0.022)	(0.022)	(0.018)	(0.025)	(0.021)	(0.018)	(0.024)
R^2	0.43	0.43	0.43	0.43	0.46	0.35	0.49	0.46	0.35
Panel B. Second-stage estimation.									
$\ln(price_{m,t+1}) - \ln(price_{m,t})$	-3.347	-0.507	10.611	-0.175	-0.123	-0.109	-0.270	-0.089	-0.071
	(13.647)	(0.335)	(137.037)	(0.180)	(0.156)	(0.118)	(0.332)	(0.160)	(0.110)
$\ln(price_{m,t})$	-0.691	-0.093	2.249	-0.023	-0.008	-0.013	-0.043	0.001	-0.000
	(2.878)	(0.073)	(28.844)	(0.040)	(0.029)	(0.031)	(0.075)	(0.031)	(0.028)
$\ln(emp_{m,t})$	0.006	-0.070^a	-0.371	-0.079^a	-0.082^a	-0.081^a	-0.076^a	-0.083^a	-0.083^a
	(0.384)	(0.018)	(3.662)	(0.011)	(0.010)	(0.010)	(0.016)	(0.011)	(0.010)
First-stage statistic	0.06	3.41	0.01	2.18	3.11	4.07	0.85	2.86	3.97
Overid. p-value				0.00	0.00	0.00	0.00	0.00	0.00
Hausman test p-value	0.01	0.01	0.00	0.40	0.98	0.58	0.83	0.69	0.99

Note: 3,801 observations for each regression, representing 181 CBSAs; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table A12: TSLS results with the log growth in ticket prices used as the endogenous regressor.

The results in Table A12 suggest a weak relationship, if any, between the instruments and ticket prices. When the three instruments are used together, the 'aircraft class' instrument is generally negative while in two cases the 'distance' instrument is positive. However, when the instruments are used individually, only the 'aircraft class' instrument is weakly significant, so this may be due to a correlation between the instruments. In the second stage, the coefficients on the change in ticket prices are not significant, though as the first stage explains little of the variation in ticket prices the second-stage results may not be meaningful. Overall, as the instruments do not have a clear effect on ticket prices, it appears that the main results are not being driven by changes in ticket prices.

A6 Relationship between employment growth and future growth in airport size

This appendix tests whether the growth in employment in a CBSA is related to growth in airport size in future periods, which could raise concerns about the instruments. This analysis is conducted by repeating the OLS and TSLS estimation of (9) and (10) with additional variables for the change in airport size in future periods. If the TSLS results show a relationship between growth in employment and growth in airport size in future periods, then this could imply that the growth in employment is caused by future changes in airport size, which would suggest that the instruments are not truly exogenous. Table A13 presents the OLS results.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.011[a] (0.003)	0.013[a] (0.003)	0.015[a] (0.003)	0.016[a] (0.003)	0.015[a] (0.003)	0.017[a] (0.003)	0.017[a] (0.003)
$\ln(A_{m,t+2}) - \ln(A_{m,t+1})$		0.011[a] (0.002)	0.012[a] (0.003)	0.014[a] (0.003)	0.013[a] (0.003)	0.015[a] (0.003)	0.015[a] (0.003)
$\ln(A_{m,t+3}) - \ln(A_{m,t+2})$			0.012[a] (0.003)	0.012[a] (0.003)	0.011[a] (0.003)	0.012[a] (0.003)	0.012[a] (0.003)
$\ln(A_{m,t+4}) - \ln(A_{m,t+3})$				0.008[a] (0.003)	0.007[a] (0.003)	0.010[a] (0.003)	0.011[a] (0.003)
$\ln(A_{m,t+5}) - \ln(A_{m,t+4})$					0.001 (0.002)	0.002 (0.002)	0.002 (0.003)
$\ln(A_{m,t+6}) - \ln(A_{m,t+5})$						0.012[a] (0.003)	0.012[a] (0.003)
$\ln(A_{m,t+7}) - \ln(A_{m,t+6})$							−0.004 (0.003)
$\ln(A_{m,t})$	−0.003[c] (0.001)	−0.000 (0.002)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)	0.005[c] (0.003)	0.005[c] (0.003)
$\ln(emp_{m,t})$	−0.074[a] (0.008)	−0.081[a] (0.009)	−0.088[a] (0.009)	−0.093[a] (0.010)	−0.096[a] (0.010)	−0.097[a] (0.010)	−0.094[a] (0.011)
R^2	0.50	0.51	0.51	0.52	0.53	0.54	0.52
Number of observations	4,344	4,163	3,982	3,801	3,620	3,439	3,258

Note: 181 CBSAs for each regression; robust standard errors clustered by CBSA in parentheses; *a*, *b*, *c* denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table A13: OLS estimation with future rates of airport growth.

The results in Table A13 indicate that employment growth in the current year is correlated with future growth in the size of the airport. Most of the coefficients on future rates of airport growth are positive and significant. The strong correlation between changes in employment and in airport size in subsequent years could be due to changes in employment leading to greater demand for air travel in the local area and thus gradual expansion of local air traffic.

Table A14 reproduces the main TSLS estimates with multiple future rates of airport growth. The regressions run in Columns 2 to 7 treat all of the variables for growth in airport size as endogenous and use the three chosen instruments for each of the respective years.

	(1) TSLS	(2) TSLS	(3) TSLS	(4) TSLS	(5) TSLS	(6) TSLS	(7) TSLS
$\ln(A_{m,t+1}) - \ln(A_{m,t})$	0.036^{a}	0.026^{a}	0.026^{a}	0.031^{a}	0.029^{a}	0.027^{a}	0.020^{b}
	(0.012)	(0.009)	(0.008)	(0.011)	(0.009)	(0.010)	(0.008)
$\ln(A_{m,t+2}) - \ln(A_{m,t+1})$		0.010	0.016^{b}	0.006	0.009	0.009	0.012
		(0.009)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)
$\ln(A_{m,t+3}) - \ln(A_{m,t+2})$			0.013	0.018^{c}	0.011	0.016	0.006
			(0.008)	(0.010)	(0.009)	(0.012)	(0.010)
$\ln(A_{m,t+4}) - \ln(A_{m,t+3})$				−0.020	−0.011	−0.018	0.007
				(0.013)	(0.009)	(0.015)	(0.014)
$\ln(A_{m,t+5}) - \ln(A_{m,t+4})$					−0.013	−0.002	-0.024^{c}
					(0.010)	(0.014)	(0.013)
$\ln(A_{m,t+6}) - \ln(A_{m,t+5})$						−0.011	0.018
						(0.014)	(0.017)
$\ln(A_{m,t+7}) - \ln(A_{m,t+6})$							-0.045^{b}
							(0.019)
$\ln(A_{m,t})$	0.002	0.002	0.005^{c}	0.002	0.001	0.000	−0.001
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
$\ln(emp_{m,t})$	-0.080^{a}	-0.084^{a}	-0.091^{a}	-0.093^{a}	-0.096^{a}	-0.096^{a}	-0.091^{a}
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
First-stage statistic	33.33	12.89	7.09	6.05	2.16	1.58	2.37
Overid. p-value	0.59	0.19	0.00	0.00	0.00	0.00	0.02
Hausman test p-value	0.00	0.16	0.61	0.01	0.02	0.12	0.03
Number of observations	4,344	4,163	3,982	3,801	3,620	3,439	3,258

Note: 181 CBSAs for each regression; robust standard errors clustered by CBSA in parentheses; a, b, c denote significance at 1%, 5%, 10%; number of departing flights used as the measure of airport size; all regressions include year and CBSA fixed effects

Table A14: TSLS estimation with future rates of airport growth.

The coefficient on the growth in airport size in the current year in Table A14 changes little as the growth rates in future years are added, while the coefficients on the future years are not clearly different from zero. Two of the coefficients for the future years are positive and significant, but two are negative and significant, while roughly equal numbers of coefficients are positive and negative in sign. Moreover, the coefficients for all years sum to a number close to 0.036 in most of the columns, so the few significant values may be explained by multicollinearity and the slight correlation between the values of the instruments in consecutive years.

It should be noted that the first stage becomes weak and the overidentification tests eventually fail as more future years are added. It is therefore difficult to draw strong conclusions from the analysis in Table A14, but there does not appear to be a strong negative or positive relationship between airport growth in future years and the current growth in employment.

A7 Industry classification from SIC and NAICS codes

Table A15 presents the classification of the employment data from the County Business Patterns into industries according to the SIC and NAICS codes. Table A16 summarizes the numbers of employees by industry in the 181 CBSAs in the sample. The employment figures are suppressed in the County Business Patterns for around 13% of the county-industry combinations. In these cases, the employment figures are estimated using the number of local firms in the industry and total county-level employment, then restricting the outcome to be within the limits specified by the suppression flag and the numbers of firms within each size range, before aggregating the employment figures by CBSA.

Industry	SIC codes	NAICS codes
Construction	15-17 ("Construction")	23 ("Construction")
Manufacturing	20-39 ("Manufacturing")	31-33 ("Manufacturing")
Wholesale and retail trade	50-51 ("Wholesale Trade") 52-59 ("Retail Trade")	42 ("Wholesale Trade") 44-45 ("Retail Trade")
Transport and utilities	40-49 ("Transportation & Public Utilities")	22 ("Utilities") 48-49 ("Transportation and Warehousing")
Other services	60-67 ("Finance, Insurance, Real Estate") 70-89 ("Services")	51 ("Information") 52 ("Finance and Insurance") 53 ("Real Estate and Rental and Leasing") 54 ("Professional, Scientific, and Technical Services") 55 ("Management of Companies and Enterprises") 56 ("Administrative and Support Services") 81 ("Other Services (except Public Administration)")

Table A15: Industry definitions from the two-digit SIC and NAICS classifications.

	Employment			
Industry	Mean	Std. dev.	Minimum	Maximum
Construction	24,287	40,145	222	370,854
Manufacturing	51,798	96,240	185	1,045,467
Wholesale and retail trade	21,043	42,203	232	530,637
Transport and utilities	69,408	135.464	215	1,370,323
Other services	170,946	347,614	1,382	3,651,004

Note: 4,525 observations of each variable, in a balanced panel of 181 CBSAs

Table A16: Summary statistics for employment by industry.