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Airports, Market Access and Local Economic Performance: Evidence from China

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Abstract
In this paper we study the effect of airports on local economic performance that arises from better access to domestic markets, using China's recent rapid air network expansion. We estimate the effects of the implied changes in access to population on measures of economic performance using a panel of counties built from administrative records and micro data on industrial firms. To mitigate endogeneity concerns we focus on a subsample of 'incidentally' affected counties, whose location midway between existing and new airports implies they not were explicitly targeted for development nor directly affected by airport operations. We also decompose market access into land-side and air-side components. Our key finding is that improved population access due to land-side distance reductions to airports increased industrial output and GDP, with an elasticity of around 0.25. An instrumental variables strategy exploiting conversion of historical military airports to civil use yields higher elasticities.

Keywords: airports, infrastructure, productivity, China
JEL Classifications: H54; O21; P25; R41

1. Introduction

Air transport is, self-evidently, an important facilitator of the movement of goods and people in and between countries across the globe. International air passengers travelled around 320 billion kilometres per month in 2014, domestic passengers around 180 billion kilometres. Measured in terms of freight tonne kilometres, air freight is 2.5 times more important for trade in goods than marine freight[1], moving around 16.5 billion freight tonne kilometres per month in 2014. As with all transport, the fundamental value of air travel and airports is in saving time. But in addition to their role in facilitating this faster leisure travel, business travel and trade, airports are also large local employers, with local workers directly and indirectly involved in supporting airport operations (Hart and McCann 2000; Brueckner 2003).

For these reasons, expansion of air transport capacity is generally regarded as a pre-requisite for economic growth in a modern economy. Airport construction or expansion is seen as a policy lever to boost cities, regions and national economies, and an inadequate airline service an obstacle to local economic development. In large developing and emerging economies with poorly established land transport, the time savings from expanding the airport network are clearly potentially large. In these settings, airports are often built and expanded with the explicit aim of improving connections to peripheral areas, stimulating economic activity in these areas and reducing inter-area disparities (World Bank 2013). However, airports are expensive pieces of infrastructure to build and to run, and there have been failures[2]. In truth, despite the policy enthusiasm, there is relatively little evidence on whether the opening of airports or expansion of airport capacity really stimulates economic development in a causal sense-or offer good value for money. Some notable early exceptions in include (Brueckner 2003; Button 1999) with more

[1] IATA 2014, OECD International Transport Forum (2013)

[2] http://www.worldfinance.com/home/europes-dead-airports-a-big-waste-of-taxpayers-money

recent contributions from (Redding et al. 2011; LeFors 2014; McGraw 2014; Sheard 2014; 2015; Blonigen and Cristea 2015).

This paper is the first large scale study to examine the economic impacts of new airports, focussing on the economic benefits brought about by reduced travel times and improved access to population. As well as being an important and interesting case in its own right, China provides an ideal case for studying the more general causal impacts of airports. Firstly, expansion of the airport network has been rapid. Starting from around 112 airports in 2000, there was a relatively unregulated expansion of 20 new airports in the early 2000s. This was followed by a more systematic programme of civil aviation infrastructure investment, with over 300 billion RMB (46 billion USD), spent constructing 38 new civil airports between 2006 and 2010 and with a further 50 planned between 2011 and 2015 (KPMG 2013). Passenger numbers in China increased by around 13% per year after 2006, with 14% per year growth in domestic travel, many times faster than major developed economies. Air freight has also grown rapidly, with an 8-9% per year growth in freight tonne kilometres, both domestic and international. By 2013, China is world's second largest air transportation market, carrying 353 million passengers and moving 16 billion tonne kilometres of freight (compared to 743 million passengers and 37 billion tonne kilometres in the US).[3] This rapid expansion means that there are many new airports, and large changes in the geographical patterns of accessibility in China, on which we can base our estimation.

As with other transport infrastructure, estimation of the causal impacts of airports on economic performance faces serious challenges. Airports are typically targeted to where there is perceived need, rather than randomly assigned across space, and places with and without airports will differ on many pre-existing dimensions. Therefore, separating out the effects of the supply of airports from other determinants of economic performance is difficult.[4] Distinguishing the

[3] Authors; own calculations from Civil Aviation Administration of China, 2006, World Bank Development Indicators 2014, IATA 2014.

[4] A full cost-benefit analysis, which would need data on the cost of input capital and resources, as well as environmental and other social benefits, is beyond the scope of this paper.

direct impacts of airport operations on the local economy from the more fundamental economic benefits of reduced transport costs is also challenging and this issue has never been addressed in the existing empirical literature. There are key elements of our research design, which push our contribution beyond what has been done before to tackle these issues. Firstly, our treatment variable is a continuous measure of population access or 'market access'. This type of index is variously referred to in the literature as market potential, population potential, effective density, or closeness centrality, dating back to Harris (1954) and recently applied in Gibbons et al (2016) and Donaldson and Hornbeck (2016). This air access index involves aggregating potential destination populations using imputed minimum journey times, from an origin county to its local airports, and from these airports to all other destination airports. Changes in this index over time occur purely because new airports change the pattern of potential air-side linkages across China from one airport to another, and because they reduce the land-side journey times from firms (or residents) to airports. A specific innovation in our paper is to decompose this index into these two components – land-side and air-side – to provide insights into the channels through which improved access operates. This innovation has relevance to transport analysis in many other contexts. As well as being well grounded in theories of market access, this index provides but finely geographically differentiated patterns of changes in treatment, due to a county's position in relation to new and existing local airports, and the changes in geographical position of its nearest airports relative to other airports in China. It is thus much more refined than the simple indicators of the presence of an airport, or distance to airport that have been used as a measure of treatment in previous studies.

The second key feature of our research design is to isolate subsets of neighbouring counties mid-way between old and new airports, that can be regarded as comparable in terms of policy targeting, and 'incidentally treated' by new airport construction. When a new airport is constructed, it evidently offers potential benefits for the places very close-by that are the potential target. But firms and people in places much further away benefit too, even if not intentionally targeted, to the extent that the new airport is closer to them than any existing airports. We use this observation to define geographical buffer zones comprising both: a) non-targeted counties that were some distance from new airports, experienced changes in the set of airports that were closest to them, and moderate – but not extreme – distance reductions to these airports; and b) comparable neighbouring counties that remained closest to existing airports and so were less affected or unaffected. Variation in changes in accessibility within these combined groups provides the identifying source of variation in our study. This aspect of the design offers at least two advantages. First and foremost, the characteristics of the counties selected in this way are, as we demonstrate empirically, uncorrelated with the intensity of changes in air access, thus mitigating the problem of biases due to endogenous policy targeting. Secondly, any impacts on economic performance arising from treatment within these incidentally affected and unaffected counties will arise predominantly through the economic benefits of market access, transport and trade costs (sometimes referred to as the 'catalytic' effect of airports in the airport economics literature). This is in contrast to impacts on counties close to new airports that can occur due to the employment opportunities offered by the operation of the airport itself (so called 'direct impacts'), the knock-on effects of airport operations on the demand for intermediate goods and services from the local economy (so called 'induced impacts') and the impact of other transport infrastructure or other local policies that were put in place to support the airport development.

Final elements in our research design are: a) a placebo test in which we compare the effects of distance reductions to airports that have been built with the effects of distance reductions to airports that are proposed for the future; and b) an instrumental variables strategy based on this location of military airports built prior to 1949 but converted to civil use. All this analysis is conducted on a unique bespoke panel dataset of counties – covering mainland counties and urban districts in China, constructed from statistical yearbooks, population census, micro data from the Annual Survey of Industrial Firms and various other web and geographical sources.

Our key finding is that improvements in air transport access generated increased industrial output (gross output and value-added), Gross Domestic Product (GDP) and fixed asset investment. However, we find little or no evidence of impacts on a range of other indicators like service sector GDP, incomes, and employment. Effects are more pronounced in smaller firms, privately owned firms and firms located in high population, but lower educated counties. The elasticities of output with respect to changes in market access are large – around 0.2-0.3. This elasticity implies a gain in industrial output of around 8% from the average national access change of over the 2001-2009 period (if one is prepared to extrapolate nationally from our results). To put this in context, the overall growth in industrial output over this period was 210%. These gains in the industrial sector are presumably attributable to cost reductions in business travel and air freight transport, and associated agglomeration economies, but we lack data to confirm the exact channels. The results on land-side versus air-side access suggest these effects on the industrial sector are primarily due to reductions in the land-side distance from counties to airports. The estimated effects of air-side availability of potential destination airports are less well determined, although we find large positive effects on GDP.

The structure of the paper is as follows. In the next section we review previous evidence on the impacts of airports on economic development. Next, section 3 explains our empirical strategy, discussing China's airport programme in more detail and setting out how we use this in our estimation. Section 4 describes our data sources and construction of the dataset. The main results are presented and discussed in Section 5 and Section 6 concludes.

2. Previous evidence

Transport infrastructure such as roads, railroads and airports, may affect the local economic activity through at least two theoretical channels at work. At the aggregated area level, improved transport access reduces trade costs and induces gains from inter and intra-industry trade through comparative advantage, specialisation and economies of scale (Ricardo, 1817; Krugman, 1980; Fujita et al., 1999; Michaels, 2008). This is especially the case in large developing countries where spatial economic disparities are substantial between peripheral and metropolitan regions (Faber 2014), and transport infrastructure improvements could contribute to city growth (Zheng and Kahn 2013), population and industrial decentralization (Baum-Snow et al. 2016) by reducing the barriers of the spatial mobility of capital and other fundamental factors (Topalova 2010). Improved transport gives rise to a diverse range of potential agglomeration mechanisms arising from closer integration with other firms, labour markets, product markets and suppliers of intermediate goods – sharing, matching and learning to use the typology of Duranton and Puga 2004. These mechanisms affect not only the efficiency of individual firms, but also the organisation of economic activity across space (Redding and Turner 2015; Lovely et al. 2005; Bel and Fageda 2008).

There is a large and growing body of work on the causal effects of roads and rail transport in developed economies (Baum-Snow 2007; Duranton and Turner 2012; Duranton et al. 2014; Redding and Turner 2015; Gibbons et al. 2016) and in developing economies including China (Zheng and Kahn 2013; Faber 2014; Baum-Snow et al. 2016; Bannerjee, Duflo and Qian 2012, Qin 2016). In contrast, the literature on air transport is so far limited to developed countries and mainly the US[5]. Dealing with the endogeneity of airport locations is the major challenge. Early examples are Button (1999) and Brueckner (2003), both whom estimate the impact of hub airports in the US on the metropolitan areas they serve using cross-sectional metropolitan area level regressions. Button finds a positive association between a city having a hub airport and high-tech employment, through some simple OLS regressions. A number of papers extend this

[5] One large strand of literature looks at a different issue, the effects of liberalization and deregulation in the airline sector on the performance of the airline industry and air networks (Borenstein 1989, 1991; Brueckner 2002, 2004, 2009; Daniel 1995; Debbage 1993; Goetz 2002; Goetz and Sutton 1998; Graham 1993; O'Kelly 1998; Shaw and Ivy 1994). For China, the focus has been on development of airport networks (Wang et al. 2014), civil aviation policy reforms (Zhang 1998; Zhang and Chen 2003; Yang et al. 2008; Zhang and Round 2008), airline market consolidation (Shaw et al. 2009) and on the geographic and socioeconomic factors affecting airport locations and traffice (Jin et al. 2004; Yao and Yang 2008).

idea, using hub locations hub locations, and centrality of a place within the spatial distribution of population, or within the spatial extent of the country, as instruments for metro airline traffic. Papers based on this method find that air traffic is associated with more service sector employment in the US (Brueckner 2003) and Italy (Percocco 2010), and with population and employment growth (Green 2007). Of course, the implicit assumption that airport hubs are randomly assigned across cities or otherwise exogenous conditional on some basic control variables is debatable. One might also have serious concerns too that centrality in the population distribution or geographical extent of a country has direct effects on economic outcomes other than through airline traffic. More recent papers have adopted an alternative approach used elsewhere in the transport literature (Duranton and Turner 2012), instrumenting airport size or location with historical plans. Sheard (2014) uses the 1944 U.S. National Airport Plan as an instrument for 2007 airport size in a cross sectional analysis, finding an impact on service sector employment. McGraw (2014) extends this idea using historical air mail networks, army air networks and civil emergency airfields to predict whether cities have an airport (the assumption being that these historical factors are precursors for full airport construction). He finds effects of airport location on population and employment growth in the tradeable sector, but not in services. All of these works are fairly silent when it comes to demonstrating that their historical instruments are genuinely uncorrelated with pre-existing area characteristics that might affect subsequent economic development, and are the designs are largely reliant on conditional exogeneity assumptions. Other methods and instruments have been tried. Sheard (2015) follows the Bartik (1991) shift-share methodology, i.e. predicting local airport traffic growth from national trends. Blonigen and Cristea (2015) employ a fixed effects methodology to look for the effects of breaks in the trends in city air traffic on income population and employment, arguing that changes in traffic in their study time window are due only to the 1978 U.S. airline industry deregulation policy. Introducing an innovation similar to one we employ in this paper, LeFors

(2014) uses a market-access index (Harris 1954, Hanson 2005) to define accessibility, although his analysis is purely cross sectional.

A notable absence in all this literature is any study that explicitly exploits the opening of new airports to estimate their impact on local economic outcomes, in a difference-in-difference design. All of the above focus on the cross sectional distribution of airports or changes in air traffic in an existing airport network. Also absent is any work on developing countries. Moreover, previous work looks only at the impact of airports on the employment and incomes of the cities in which they are located, sometimes with extensions to look at spillovers (Percocco 2010) or to estimate multiplier effects (Sheard 2015). None try to separate out to what extent the impacts are attributable to travel time reductions (or 'induced' impacts in the airport economic literature) – the main purpose of air transport. Our paper offers contributions on all these dimensions.

3. Research design

3.1 China's national airport system

In the post-'cold war' era China's economy and its spending on transport infrastructure grew rapidly. Investment in highways and railways increased from below 2% of GDP in the early 1990s to around 6% by the 2000s, a share which is well above the 1% share typical in developed countries (OECD International Transport Forum 2012) and which puts China top among developing countries. Nevertheless, in the early 2000s the Chinese air network was still widely considered under-developed, notorious for their overcrowding, poor connectivity, and heavy reliance on few hub cities (see Zhang 1998; Wang and Jin 2007).

The institutional environment in post-war China contributed to this under-development of the air transport network. Whereas other Asian countries developed civil aviation sectors to meet the demands of rapid industrialisation, China committed its resources to military-related infrastructure. The Civil Aviation Administration of China (CAAC) was founded in 1954 as a branch office under the Military Commission and was responsible for operating airports and airlines. But, as with the Soviet system, the air transport network was built primarily to link major cities, to serve the needs of government officials and military defence. Airports and airlines were not intended to improve firm productivity and facilitate business and trade.

In the late 1980s, the central state government launched a set of waves of market-oriented reforms to the air transportation system and the CAAC was separated from the military control. The first codified state involvement in developing a national civil aviation system came with the Civil Aviation Act of 1995. This legislation instructed the CAAC to formulate a series of plans for developing airline services and managing airport facilities. Initially, as restrictions on state-owned business and personal travel continued during the 1990s and the early 2000s, air travel was not widely used by firms and civilian households. Land-based transport (highways and railways) remained the main channels for transporting goods and people. However, as industrialisation and urbanisation proceeded, there was a gradual relaxation of air-ticket restrictions and an increased use of private-public partnership mechanisms to finance new airport facilities. This triggered incentives for local governments to build their own airports, and resulted in rapid, but unregulated, expansion of the network. Even so, all China's airports and nearly all internal airlines are still state-run enterprises and there is not an 'open skies' air transport policy. A few low cost private operators have emerged on internal routes. International airlines can only operate at some of the main hub airports.

In 2003, greater control over airport development was transferred back to the CAAC from the provinces and regions, with the aim of improving the efficiency of airport investments and to avoid excess capacity in already developed areas. The CAAC began to put in place a centralised national airport allocation plan, which regulated the development of airport transport for the period 2006-2020. The plan was officially published until 2008, after the agreement by the State Council Committee (CAAC, 2008). However, the plan's regulations became effective well before 2006 and covered all airports opening from 2006 onwards. The aims of this plan were to develop a strategic airport network that would meet interregional air travel demands, promote cooperation of different ethnic groups and serve national defence needs[6]. Phase 1 of the plane covered development from 2006-2011, and phase 2 covered 2011-2020. In the first phase, more than 40 airports were built, with funding of over 300 billion RMB from the National Development and Reform Commission of China and provincial and local government agencies. These airports were built rapidly, with construction often taking only 18 months between start and completion. One useful feature of this plan was that it aimed to restrict the development of multiple airports in close proximity, with a target of 200km between new and existing airports. Although little is known about whether this guidance was explicitly enforced, it does imply that in the second period related to our study, from 2006 to 2010, there was a policy rule which offset the tendency for new airports to be built in politically favoured or economically prosperous areas.

Our empirical work will estimate the impact of new airports on economic development in China, exploiting this rapid but scattered development of regional airports in China to estimate the impact of marginal improvements in air accessibility on non-targeted counties. Our approach is a variant of the incidental treatment approach (sometimes referred to as an 'inconsequential' units method) that is commonly applied in road and rail transport analysis. The exact implementation is described in the next section.

3.2 Empirical specification

The starting point for our empirical analysis is a panel fixed-effects specification in which we investigate whether counties which became more accessible by air as a result of new airport construction from the early to late 2000s, experienced bigger changes in economic performance over this period. We implement this through a regression of long time interval changes in outcomes on the corresponding change in air accessibility for counties in mainland China:

[6] See http://www.caac.gov.cn/i1/I2/200808/t20080819_18371.html

$$\Delta \ln y_{it} = \alpha + \beta \cdot \Delta \ln air_{it} + x_{it}'\gamma + \varepsilon_{it} \qquad (1)$$

where, $\Delta \log y_{it}$ denotes the change over time in the outcome variable up to year *t,* i.e. $\Delta \ln y_{it} = \ln y_{it} - \ln y_{it-s}$, where s ranges between 4 and 9 depending on the data used. The treatment variable is Δair_{it} and is the corresponding one-year lagged change over time in air-accessibility within panel units of analysis *i* (we suppress the one year lag in the notation for simplicity). The panel units *(i)* are county or county-by-industry units. The time interval for Δ and the number of periods (*t*) varies according to the underlying data as explained when we present the empirical results. The optional control variables in the regression (x_{it}) include flexible controls for general geographic factors that affect the changes over time within panel units (e.g. fixed effects for nearest airport in the base period, province dummies or geographic and socioeconomic characteristics). When we estimate from industrial firm survey data, equation (1) corresponds to a time-differenced aggregated production function at 2-digit-by-county level. In this case, we control for changes in firm inputs (using a quadratic in ln employment and ln total assets, i.e. a translog production function) plus 2-digit industry dummies to allow for industry specific time trends. Unobservables are represented, as usual by ε_i .

3.2.1 Air market access

The treatment variable $\Delta \ln air_i$ is the change in (ln) market access by air and has the following structure:

$$Air_{it} = \sum_{j \in J_{it}} \left(\sum_{k \in K_t} pop_k \times airtime_{jk}^{-1} \right)_j \times landtime_{ij}^{-1} \qquad (2)$$

This index is based on a standard inverse-distance weighted market access index. First we calculate air market access for each airport (*j*), by aggregating the populations in counties with potential destination airports available in China in period t ($k \in K_t$), discounting by imputed flight times $airtime_{jkt}$. This is the term in brackets. For each county (*i*) we then aggregate this airport-based air market access in the set of nearest neighbour airports ($j \in J_{it}$), using imputed land journey times from the county to the airport. The set of nearest neighbour airports J_{it} consists of the nearest 5 (by straight line distance) in our preferred specification, although we check robustness to this assumption, and to other variants in the functional form. More detail on construction of this index is given in Section 4.

Note, two elements change from one year to the next: the overall set of airports in the set K_t, and the set of local airports to each county J_{it}. The air travel times and land travel times for specific airport-airport or county-airport pair do not change over time and are based on straight line distance, adjusted for typical travel speeds and connection times, fixed over time (details in Section 3.2.1). The population weights pop_k are from the 2000 population census so are also fixed over time. Therefore the only variation over time in the air market access index comes from variation in the set of airports available in China (K_t) and local to each county (J_{it}). It is important to note that although the changes in K_t are the same everywhere in China, the impact of changes in K_t in equation (2) varies across space because it interacts with the set of nearest neighbour airports for each county because different sets or airports in J_{it} have different distances to the global set of airports K_t .

There are necessary approximations in this index. Firstly, we do not consider market access outside of China; our analysis refers only to internal market access. Secondly, we do not use actual air-side travel times or available flight routes, because: a) we do not have the information for the full set of airports; b) the choice of routes that are operated is potentially endogenous to demand and local economic performance. We therefore assume that flights are possible in principle from any airport to any other. Thirdly, we do not use actual land transportation network or travel times because: a) we do not have historical information on the road network; and b) there has been a rapid development of the highway and rail system in China, and the land side travel speeds and infrastructure and hence an index constructed using actual land travel times is itself potentially endogenous to local economic performance. Lastly, the destination population weights are the census populations in the counties in which the airports are located. In principle, we could add a step and aggregate neighbouring groups of destination counties back to destination airports using land-side travel times to get airport specific pop_a. While initially attractive, it turns out to be a bad idea because one ends up attaching an origin county's own and neighbour counties' populations into its own external air market access index, when origin and destination airports are moderately close together. As an additional step to avoid this problem, we restrict attention to airport-to-airport routes where the implied flight times are greater than 15 minutes.

A useful feature of this index is that it can be decomposed into components attributable to changes in availability of airports in China as a whole (K_t), and changes in the availability of airports local to a given county (J_{it}). Representing (2) as $Air_{it} = A(K_t, J_{it})$ and the change $\Delta \ln Air_{it} = \ln A(K_t, J_{it}) - \ln A(K_{t-s}, J_{it-s})$, we can by construction write:

$$\Delta \ln Air_{it} = \left\{ \ln A(K_t, J_{it}) - \ln A(K_t, J_{it-s}) \right\} + \left\{ \ln A(K_t, J_{it-s}) - \ln A(K_{t-s}, J_{it-s}) \right\} \quad (3)$$

The first term on the right hand side is the imputed land-side change in market access, that is the change in market access occurring because a county has a new set of nearest local airports, holding the availability of other airports in China constant at its end of period (t) level. The second term on the right hand side is the air-side change in market access, holding the set of local airports constant, but changing the availability of airports in the rest of China. These components can included as separate regressors in (1) to estimate their separate contributions.

3.3 Identification issues

Ordinary least squares estimates of β in equation (1) are unlikely to yield estimates that can reliably interpreted as causal, even with an extensive set of controls for observables. The fundamental threat to identification of the causal effect of improved market access through airports is that new airport locations are endogenously determined. As usual in this type of fixed effects/difference-in-difference analysis, the key issues are: a) initial conditions and pre-existing trends in economic performance between more and less treated counties; and b) unobserved shocks to performance occurring at the same time as the change in airport access. Both factors imply that less-treated counties provide poor counterfactuals for more-treated counties.

Differences in pre-existing conditions may arise through disparities in counties' physical geography or the level of economic development or through institutional processes. For example, local governments may be more likely to seek permission to build an airport and be successful in securing funding in places where there is growing demand or which are politically important. The preferences and effectiveness of local government agents may also influence the planning and building process and influence local growth via other policy channels.

The first element in our identification strategy exploits putatively random variation in changes in access induced by the changing geometric relationship between counties and the set of existing airports and new airports that influence market access index in different years (equation (2)). The key element of this design is that we focus only on counties that are within spatial buffer zones, bordering the mid-line between existing airports at the beginning of a time interval (t-s), and new airports constructed over the time interval up to year (between t-s and t). These zones comprise two groups of counties: 1) places that are largely unaffected in terms of land-side transport costs by new local airport development because their existing nearest airport remains the closest, although they are affected by the air-side network expansion; and 2) neighbouring counties who experience a reduction in distance to their nearest airport, so experience land-side cost reductions plus air-side gains.

The rationale for this focus is three fold. Firstly it means the group of counties we select are not the specific targets of airport development and we can exclude counties with new airports or near new airports from the analysis. Secondly, it means the counties are more likely to be comparable to each other because they are geographically neighbouring. We include fixed effects (in equation 2) for groups of counties sharing the same nearest existing airport to further ensure we are comparing relatively localised groups of counties. Thirdly, it implies that despite the counties being neighbouring changes in air access (as in equation (2)) occur due to changes in the set of nearest-neighbour airports (J_{it} in equation (2)), and these changes occur randomly and discontinuously depending on a county's position relative to existing and new airports.[7]

To illustrate these points, Figure 1 shows a highly stylised example. Panel A shows the catchment areas of 3 existing airports, assuming agents always choose their nearest airport. Panel B, illustrates the new catchment area from construction of new airport 4 (shown by the triangle), one a number of new airports, the rest of which are elsewhere and not shown. Some places formerly in the catchment area of airports 1, 2 and 3 switch to airport 4, while others do not depending on their relative positions. The changes in market access even in this simple example are complex. Places still in the catchment areas of airports 1-3 experience no land-side improvements because they remain closer to airports 1, 2, or 3 than airport 4. However, they experience air-side market access improvements due to expansion of the network elsewhere (including airport 4). Places now in the catchment area of airport 4 experience a change in the air-side market access too, but also experience a land-side improvement in air market access because the distance to the nearest airport has changed. Illustrative distance reduction contours are shown in Panel B. Evidently, the distance reductions increase with proximity to the new airport within catchment area 4, so a distance buffer is necessary (Panel C, shown for a cutoff at 60% distance reduction) to ensure that places close to new airports and directly targeted or affected are excluded. We make this distance buffer symmetric around the mid-way line catchment area boundaries to ensure that we also exclude counties that are close to existing airports or are remote from all airports and any potential influence.

[7] There is thus a flavour of a spatial regression discontinuity design in this setup, with the mid-way line between existing and new airports providing a discontinuity. However this analogy is inexact, given two places literally co-located in space cannot experience different changes in airport access, so estimation requires variation in the distance away from the mid-line towards and away from new airports.

Donaldson and Horneck (2016) suggest changes in market access induced by changes in a transport network that are not local to an origin are likely unrelated to be related to economic conditions in that origin, so could provide one useful source of identification. Our air-side market index has this property. As can be seen from Figure 1, this in principle provides a better source of identification in our context than land-side changes, in that it changes discontinuously as we move from one catchment area to the next. Unfortunately, a market access measure based on global changes in the network will, by construction, not vary very rapidly over space because the addition of a new destination will have a similar impact on two origins that are close together (unless the network is highly fragmented so that the routes to reach that destination are very different for each of those two origins; this is not the case in our context since we assume all airports are potentially connected to all others). The changes in air-side market access across airport catchment area boundaries are therefore small. More generally, air-side market access varies smoothly over space so it is difficult to disentangle its effects from more general spatial trends. However, we will show some results relating to air-side market access.

Specific historical institutional features or policy rules are frequently used as instruments in the transport literature (Duranton and Turner, 2012; McGraw 2014; Baum-Snow et al. 2016). As a check on the robustness of our main findings, we devise one such instrument using the location of airports that were constructed prior to 1949 for war purposes, some of which were subsequently converted to civil or mixed civil/military uses. Distance to the nearest military airport that was converted to civil use over our study (9 airports) period therefore provides a predictor of changes in distance to the nearest civil airport and a potential instrument. The justification of this instrument is that the location of the military airports was chosen for strategic reasons on non-economic grounds, and their availability for civil use was due to changes in Chinese military regions[8] and national defence priorities in the post-Mao era. The location of military airports converting to civil use is therefore plausibly exogenous to local economic

[8] https://en.wikipedia.org/wiki/List_of_military_regions_of_the_National_Revolutionary_Army

performance. A typical case is Kunming airport which was built in the 1930s for air force pilot training in the conflict against the Japanese during the Second World War. It was later converted to civil use, transporting essential freight, political officials and state enterprise resources in the early years of People's Republic of China. The underlying assumption behind this instrument is that conversion is driven by military redundancy rather than local economic demand, and we provide evidence that it is not systematically correlated with factors affecting industrial growth.[9]

4. Data

Our data is built up from a number of sources. The geographical unit of analysis is mainland counties, based on 2004 boundaries, using Geo-referenced county boundary data from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences. Our intention for using the county boundary data is to generate spatial polygon units that are able to cover all the prefecture cities and municipalities in mainland China. However, due to the complexity of Chinese local government hierarchies, it should be noted that all polygon units are county-level administrative units except for: (1) urban districts administered by the four provincial-equivalent ranked municipalities, namely Beijing, Shanghai, Tian-jin, and Chongqing, as they are directly governed by municipalities; (2) former counties such as Dongwan that have been upgraded into (semi-) prefecture city administrative units, and (3) traditional urban districts (shi xia qu) in prefecture cities that have been aggregated into one polygon so as to avoid the influence of internal administrative boundary changes during the study period. Changes in local government hierarchies and their impacts is discussed in Li et al. 2016. Our empirical specifications explore the results' sensitivity to alternative county sub-samples.

[9] In a previous iteration of this research we tried to exploit policy guidance that stated that new airports should not be built closer than 200km to existing airports, which potentially generates useful discontinuities. However, it turned out that this rule was not binding, so provided no implicit instruments for identification. We also tried distances to the stock of military airports at the beginning of our period, although this proved to be too weak an instrument to be useful in practice.

Our primary source for firm performance is micro data from the Annual Survey of Industrial Firms (ASIF) from 2001-2007 and 2009. This firm-level survey is collected by the National Bureau of Statistics and covers all large industrial firms (manufacturing, mining and energy) in China in both private and public sectors. The survey covers firms with annual sales of five million RMBs or more (about $0.75 million). This covers around 70% of industrial employment and 90% of industrial output (Brandt et al. 2012) and has been widely used for studying spatial policies and manufacturing in China (Ding et al 2016, Zheng et al., 2015, Lu et al., 2015). [10] There are around 151,000 observations in 2001 rising to 300,000 in 2007. The survey has a firm level panel element up to 2007, although firms enter and exit according to their annual sales due to the minimum size sampling rule. Firm identifiers are not available after 2007. We therefore do not exploit the firm level panel dimension, but aggregate to county-by-industry-by-year cells using 2-digit industry codes (which gives 40 unique industries). Up to 2007, these data include variables for employment, wages, capital, total fixed assets, gross output, value added, profits, plus indicators of firm ownership. After 2007 the range of economic variables is more limited, with gross output providing the main useful indicator of economic output, and employment and fixed assets the key inputs. For most of the analysis we use data from 2001, 2005 and 2009 and focus on gross industrial output (the value of sales of products, plus the value of any processing that the firm does under contract for others, plus the value of the change in inventories), although we also use data up to 2007 to look at value added and wages which do not appear in the 2009 data.

A range of other economic variables covering GDP, employment, incomes, consumption and investment come from the China Statistical Yearbooks for the Regional Economy (County-Level) for 2002-2010 and the China Economic and Social Development Statistical Database (constructed by the China National Knowledge Infrastructure System and accessed via the Ji

[10] The industrial firm data are similar to the Longitudinal Research Database in the US and the Annual Respondents Database in the UK.

Nan University). This comprehensive dataset of official statistics at county level, covering all of mainland China, is unique and required considerable data collection and cleaning effort. Previous work has either used county data with uncomplete geographical coverage or data at prefecture or province level. Although questions can be raised about the reliability of official local statistics, due to potential data manipulation, recent studies (i.e. Au and Henderson 2006; Faber 2014, Qin 2016) suggest that GDP and other key socioeconomic variables at the local level are of high quality.

Additional data include variables from the 1990, 2000 and 2010 population census (population, population over 15/16, high school educated, employment in different sectors, unemployment), plus geographic and climate variables from and the National Geomatics Center of China and National Atmospheric Administration of China. Price deflators at provincial level come from the National Statistics Office.

Airport data come from the statistics bulletin of the CAAC (2011). This is a comprehensive inventory of the operational attributes of civil airports in mainland China, excluding Hong Kong, Macao and Taiwan. The information we use includes the geographical coordinates, year opened for commercial flights, whether the airport has international flights. The 172 airports[11] with regular commercial flights open by the end of 2010 form the basis for our air market access calculations. Information, was cross-checked with the Baidu website (https://baike.baidu.com/), Wikipedia website (https://www.wikipedia.org/) and aerial photographs from Google Earth to check geocoding.

Construction of the air market access index in (2) requires three components. The county populations in 2000, an airport-airport flight time matrix and an estimate of the journey times over land from places within a county to each airport. To obtain an airport-airport flight time matrix, distances between airports were calculated using a GIS, and converted into imputed flight times using an assumed average flight speed of 800 kilometers per hour. Airport-to-airport

[11] We combine airports in Beijing and Shanghai where there are two airports in close proximity serving one city.

links with journey times of less than 15 minutes are dropped, and 1 hour is added to all links to allow for embarkation and disembarkation. Airport-specific population-based market access indicators are calculated for each year (depending on which airports are open) using the formula in brackets in equation 2 and the year 2000 populations of the counties in which airports are located. This is a standard population potential index (Harris 1954).

To obtain approximate land-side county to airport journey times, we generated a set of random points within counties in a GIS, with the number of points proportional to land area, a minimum of 3 and a maximum of 200. Straight line distances from each of these points to each airport are then transformed into approximate road travel times assuming 'Manhattan' distances ($\sqrt{2} \times$ straight line distance) and a speed of 65km per hour. For each year, these point-airport times are then used to discount the airport-specific market access measures calculated as described above. These discounted market access measures, at the nearest *J* airports to each point in a given year, are summed up within counties to give county-year-specific air market access (dividing by the number of points in a county to avoid double counting). The average point-airport distance for each county is used as the county-airport distance. As standard we set *J* to 5, so the county air market access index represents the market available from the five nearest airports, where each airport's own market access indicator is discounted by land-side distance. Note, to obtain the land-side and air-side specific indices of equation (3), we simply use the airport-specific market access measures for year *t*, but only the set of local airports available in year t-s when aggregating up to counties for year *t*.

These data sources and air market access variables are merged into three different estimation datasets for use in different parts of the analysis. We append the 2001, 2005 and 2009 years from the ASIF and merge these with air market access measures for 2000, 2004 and 2008. This estimation dataset allows to look at the effects of the air network expansion from 2000-2008 on the performance of large industrial firms from 2001-2009, in two 5 year periods. To look at value-added and wages, we can only use ASIF data up to 2007, so we merge access variables from 2000 to 2001 ASIF data and access variables from 2006 to 2007 ASIF data, and work with a single 6-year interval. For analysis of the county statistical yearbook data, we use the county data for 2002, 2006 and 2010 and merge this to air market access data from 2001, 2005 and 2009, allowing us to look at changes in outcomes in two 5 year periods from 2002 to 2010. Lastly we join data on air market access changes between 2000 and 2009 to census data from 2000 and on the changes in census population between 1990 and 2000 in order to check for correlation between air market access changes and pre-existing county characteristics and trends.

5. Results

5.1 Maps and descriptive statistics

We look first at the patterns of airport development and the implied air market access changes. Figure 2 shows the distribution of airports across China, grouped by opening date. For obvious reasons, there are more airports in the more densely populated and developed east of the country, but there are no clear patterns in way the network has evolved over time. Airports were widely scattered prior to 2001. New airports built from 2002-2005 and from 2006-2010 were also widely scattered and their locations appear to be driven by a process of filling in gaps in the network rather than targeting towards specific regions.

The upper panel of Figure 3 translates this evolution in the airport network into air market access changes over these two periods, where market access is constructed from county populations, imputed airport-airport flight times and imputed county-airport land travel times as described in Sections 3.2.1and 4. The separate categories in the map correspond to the semi-quartiles of the distribution. The changes are spread over wide areas and there are nuanced patterns, although as we would expect, the biggest changes are clustered close to the new airports. As discussed in Section 3.3 it is unlikely that these general patterns could be considered unrelated to pre-existing local economic performance. The lower panel of Figure 3 restricts the sample to our incidentally treated counties, mid-way between old and new airports. Specifically, we restrict to counties for which the absolute difference between the distance to the nearest new airport and the nearest new airport is at most 60%. The market access changes shown are the residuals from a regression of the market access changes in the upper panel on dummies (fixed effects) indicating groups of counties that share the same nearest airport at the beginning of the period. This illustrates the variation that we will use to identify the impacts of air market access on economic performance in our regressions: the variation in market access within the incidentally treated subset of counties, conditional on fixed effects for nearest airports in the base period (interacted with a period dummy when we pool the two periods). By construction the sets of incidentally treated counties tends to form rings around new airports, but as can be seen, the residual changes in access within these zones appear quite random and show nuanced variation even within groups of counties that are at a similar distance to a new airport.

As discussed in Section 3.2.1, overall air market access can be decomposed additively into air-side and land-side components. Figure 4 illustrates these separate components, for airports constructed from 2006-2009 (i.e. they add up to the pattern in the right top hand panel of Figure 3). The left hand panel shows that, as expected, the air-side changes driven by new airport destinations vary smoothly over space. There is a general east west trend with bigger accessibility changes in the west, as more airport destinations in the populous east became available. The right hand panel illustrates the land side access changes which are driven by distance reductions from county to airport. Unsurprisingly, most of the localised variation in Figure 3 comes from these land-side accessibility changes.

Table 1 summarises the key variables used in our analysis. The top panel summarises the estimation data for the industrial firms analysis (a 2-digit industry by county by year panel), the bottom panel summarises the county statistical yearbooks panel. In both cases we first report figures for the full sample and secondly for the sample restricted to incidentally treated counties (according to our definition that the absolute difference between old and new airports is less than 60% of the distance to the old one). The maximum number of counties represented in these data is 2387, but the number represented in the estimation samples varies. There are 1915 counties with non-missing data in the full industrial firms panel, falling to 650 in one or other or the two periods when we restrict to the incidentally treated group. Not all industries are represented in each county (a 2-digit industry must be represented in a county in 2001 and 2005 or 2005 and 2009 to be included in the sample). In the county yearbook derived data, there are 2080 counties in the full sample, falling to 787 represented in the two periods in the incidentally treated sample.

The top 8 rows present a range of figures related to the change in distance to local airports and the change in air accessibility. The baseline absolute level of air market access in row 1 in each set has no particular absolute meaning, but comparing the full and incidentally treated groups we can see that access was initially around 30% lower in the latter. This is because by construction, the incidentally treated counties are closer to new airports, which will in turn tend to be distant from old airports. The average change in air access from the beginning to the end of each 5 year period is, for similar reasons much higher in the incidentally treated group than the full sample: 31% compared to 15% when we look at changes in the industrial firms panel (spanning 2001-2009), 30% compared to 18% in the county statistical panel (spanning 2002-2010). Note there is little difference in the means when we compare air market access based on 5 nearest airports or just one closest airport, although the standard deviation of the 5-nearest-airport based index is lower because averaging over 5 nearest airports smooths out the variation across space. Rows 4 and 5 in each panel show the land-side and air-side components of the population based air market access index. Note, in line with Figure 4, there is much less variation in air-side market access between counties than there is land-side market access, and land-side market access comprises a much bigger share of the total in the incidentally treated group. Rows 6 and 7 show that, by construction, the geographically restricted sample is further away on average from existing airports at the begging and end of each period, although the average distance reduction is greater.

Evidently the incidentally treated group is not perfectly representative of China as a whole, with industrial output around 15% lower and overall GDP around 35% lower. Average populations are 23-25% lower and the share of high school educated is lower in the incidentally treated group. However, the sector shares of GDP are quite similar in the two samples, with 42-43% in the secondary sector (mining and manufacturing) and 34% in the tertiary sector (services). Note, the primary sector is agriculture, forestry and fishery. Any differences across the samples are not too surprising given the patterns in Figure 3 but might raise concerns about the representativeness of the results presented in the subsequent regression analysis. However, it should be emphasised that the aim here, as in any 'quasi experimental' analysis, is to estimate causal effects from sub-groups of the data where the variation in policy can be considered exogenous or 'as good as random' (e.g. around the cut-off in a regression discontinuity design, or for the groups who respond to the instrument in an IV analysis). This necessarily implies a certain degree of non-representativeness. We have just made this issue explicit by our sample restrictions.

Table 2 assesses the validity of focussing on a sub-sample of incidentally treated counties and conditioning on nearest existing airport fixed effects with a series of 'balancing tests'. The aim is to detect to what extent the counties that experience a bigger change in market access are comparable to those that experience a smaller change in market access, along a range of pre-existing dimensions. These are regressions of fixed over-time variables (mostly taken from the population census in 2000, plus some geographic factors) on the 2000-2009 change in air market access. There are two sets of results for each dependent variable, one for the full sample (where there are no control variables in the regression) and one for the incidentally treated subsample (where fixed effects for the nearest airport in 2000 are included).

The patterns are striking. In most cases there are large and significant associations between changes in air access and the initial conditions. Counties with bigger improvements in air access had higher shares of employment in agriculture and mining and lower shares in manufacturing, construction and services. They were also at higher elevations, cooler and dryer. These counties also had lower populations, higher population growth, a lower initial level and less growth in the proportion high school educated. When we restrict the sample geographically and control for nearest-existing-airport fixed effects these patterns largely vanish: all the coefficients become small and/or non-significant. The implication is that the patterns of residual air market access changes in this incidentally treated subgroup – as illustrated in the lower panel of Figure 3 – are random with respect to observable initial county characteristics.

5.2 Main regression results

We turn now to the main results from the regressions of changes in industrial firm output on changes in air market access. Table 3 presents the fundamental results of this analysis and the key results of the paper. All results are coefficients and standard errors from regression estimates of equation (1), using the industry-by-county-by year panel, subject to various specification changes. Standard errors are clustered on nearest airport at the end of each period so they are robust spatial and temporal autocorrelation within nearest-airport groups. The dependent variable is the change in gross industrial output over the period and there are two periods 2001-2005 and 2005-2009. All specifications include controls for firm employment and fixed assets (a second order polynomial in the natural logs of these variables), plus dummies for industry (2-digit). Columns 1 and 2 present estimates on the full sample, firstly with no geographical controls, secondly with fixed effects for the nearest pre-existing airport in 2000 interacted with a time period dummy. Note, these fixed effects in the change-based regression control for differences in trends, not levels, of market access. There is no association between change in air market access and change in industrial firm output in either specification, though the differences in pre-existing characteristics in Table 2 imply that there is no justification for reading these estimates as causal.

Columns 3-7, by contrast, report results for the incidentally treated subsample, controlling for nearest pre-existing airport fixed effects. Column 4 includes in addition, a control for the initial air market access at the beginning of each period, and column 5 adds in a range of census variables described in the table notes to control for trends related to initial conditions. Column 6 replaces the census variables with a set of 40 dummies for quantiles of the distribution of the 1990-2000 population changes, in order to control flexibly for pre-treatment trends in population. Column 7 uses instead a set of around 31 province dummies, so there are controls for time trends related to nearest pre-existing airport and to province. The coefficient on air market access in all these regressions is fairly stable at around 0.20-0.28, implying that the choice of geographical control variables is largely irrelevant, and reinforcing the argument that the air-access changes in these specifications are as good as random. Comparing the results in columns 3 and 4 with columns 1 and 2 implies that airports were targeted towards areas which had lower rates of industrial growth and so estimates based on the full sample are severely downward biased (as we saw in Table 2, they were evidently targeted towards areas with lower manufacturing employment, higher agricultural employment and slower growth in the high-school educated share).

Table 4 presents similar specifications for the 2001-2007 change in the industrial firm data, where we can look at value-added (i.e. gross output minus intermediate costs) and wages which are not available in later years. Only specifications for the incidentally treated group are reported. For value-added, the coefficients are reassuringly close to those in Table 3, even though this is for a different time span. Again the coefficients are insensitive to the choice of control variable set. However, when we look at average wages, we find no effects of market access. Evidently, market access appears to be increasing industrial productivity, but the benefits are not accruing to workers in terms of higher wages. This may in part be explained by workers' wages being linked to job ranks rather than to productivity in Chinese state ownership enterprises.

A wider range of outcomes is available from the county statistical yearbook data, and we report the results from this analysis in Table 5. Given the relative insensitivity of the results to the choice of control variables, we present only those for the more parsimonious specification where we control for nearest initial airport fixed effects and initial air market access (in the regression of changes in outcomes on changes in market access). The coefficients in Table 5 present a mixed picture, but one thing is clear: the effects observed in the industrial data analysis are borne out by the results on secondary sector GDP from the official county yearbook statistical data. Note, these are independent data sources, so this is not a mechanical artefact of the data. Overall GDP responds too, but only because of the effects on secondary sector GDP. There are no sizeable or significant impacts on other sectors.

There are no impacts on urban income or consumption (consistent with the result for wages in Table 4), nor any general changes in rural or urban employment. Similarly, we find no impact on employment in the industrial firms data (estimates not tabulated). A striking finding in Table 5 is the effect on fixed asset investment, which here means investment in factories, plant, housing and infrastructure in the private and state sectors. This finding might suggest that increases in air market access have been accompanied by increased capital intensity in production, although we found no evidence of this when looking at total assets in the ASIF dataset (estimates not tabulated). The result is suggestive of the fundamental idea that one of the main impacts of transport-induced access improvements is land use change, because it makes more land valuable for development (Redding and Turner 2015, Baum-Snow et al 2016). Better data is required on land use to shed further light on this issue. One concern might be that the coefficient on fixed asset investment is due to public investment in infrastructure related to the airport and its operations (i.e. our sample restrictions have not successfully isolated incidentally treated counties. However, further restricting the sample to counties at least 100km from old and new airports tends to increase the coefficient rather than reduce it, so direct impacts from airport infrastructure seem unlikely. Note too that there is no evidence of any associated increase in local government expenditures (Column 10).

5.3 Robustness tests, placebo tests and instrumental variables estimates

The key result so far is that air market access increased industrial output, and we now explore the robustness of this finding to sample and specification changes, and an alternative identification strategy. A crucial question is to what extent our findings – specific to the 'incidentally treated' – subgroup are sensitive to how we define this group. Our main results used the restriction that the difference in distance between the nearest old and new airports is less than 60% of the distance to the old one. This choice is governed by the trade-off between using comparable counties, mid-way between old and new airports, and sample size. Table 6 starts by presenting results on the sensitivity to this choice of distance buffer. Column 1 presents the preferred estimate from Table 3. Columns 2-4 show that as we reduce the width of the sample around the mid-way line – which implies that the coefficients are more reliably identified, given the counties will be closer and more comparable to each other, but further away from new and existing airports. The coefficients become marginally larger but less precisely estimated due to smaller sample sizes; there is no evidence that narrowing the sample would change the estimates substantively. Conversely as we widen the geographical zone, the coefficient falls as we would expect given the results for the full sample in Table 3 and the balancing tests in Table 2: comparing counties across a wider geographic sample is inappropriate, given airport targeting.

The remaining columns restrict the sample or add modifications to the specification in other ways. Introducing fixed effects for nearest new airports (column 5) changes nothing relative to the baseline results. One concern might be the coincident development of other infrastructure, such as high speed rail (Qin 2016), but dropping counties crossed by high speed rail lines from our sample makes little difference (column 6). We also dropped aggregated city cores (shi xia qu) and urban district units (qu) from the sample to ensure that the aggregations described in Section 4 do not cause problems (result not tabulated). Evidently there is some sensitivity to other sample choices. Restricting to counties further away from airports (column 7 and 8) or trimming out the largest and smallest access changes (column 9) yields bigger coefficients; trimming the top and bottom of the distribution of gross output reduces them (column 10). However, given the standard errors, this variation in different samples is unsurprising. If anything, the results suggest that our main estimates are conservative, and still downward biased by targeting of airports to areas with slower industrial growth.

Columns 11 and 12, compare the effects in the two periods in our data. Clearly, much of the action is from the 2005-2009 period which is unsurprising given this period saw the fastest growth in airports (38 versus 20 in the earlier period), although a test of the difference in these coefficients does not reject equality.

Further extending the assessment of the robustness, Table 7 explores alternative measures of air market access. Column 1 resorts to a simple metric: the reduction in (ln) distance to nearest airport, in the time honoured fashion following Gibbons and Machin (2005) for rail stations. The sign is in the direction we expect (a reduction in distance increases output) and the elasticity is minus 0.11. This alternative measure lends itself to a straightforward placebo test, to further rule out biases from policy targeting of airports to growing places. In this test in column 2 we include an additional variable which is the reduction in (ln) distance to nearest airport, assuming that the new airports are those that are planned between 2010 and 2020, rather than those that have actually been constructed by 2010. A significant effect from future airports would undermine the claim that the distance reduction coefficients for completed airports are causal, but we see a very small insignificant coefficient and the coefficient on actual airport distance reductions is unchanged.

Column 3 in Table 7 is the air market access index based on the nearest airport, rather than the nearest 5. As with column 1, most the action here comes from changes in distance to the nearest airport (though with weights dependent on the air-side market access of the nearest airport). The elasticity has similar implications to column 1. Note the lower magnitude (less than half) of these coefficients relative to our main results is a scaling issue. The standard deviation of the distance reduction and change in air market access based on the nearest airport is more than double that of the air market access change based on the nearest 5. Hence, if we were to think in terms of the impact of a standardised one-standard deviation change in the air market access induced by the airport policy, the impacts are all very similar.

The fourth column of Table 7 is intended to allay any concerns that our results are influenced by the population weights that enter via the airport destinations in the market access index (equation 2). The index of market access now is removes these weights so equation 2 becomes an index of non-node weighted network closeness centrality (basically counting up nodes with inverse distance weights). The coefficient on this index is nearly identical to that from our preferred specification. Lastly column 5 changes the assumptions about travel speeds underlying the market access, reducing airspeed by 25% to 600km/h, increasing land speed to 75km/h, increasing assumed embarkation/disembarkation times to 1.5hrs and dropping all air journeys less than 0.5hrs (300km). The resulting point estimate is virtually unchanged.

Finally in this section, Table 8 presents instrumental variables estimates using the location of military airports, built before 1949, as an instrument for the change in market access. The identifying assumption is that their location was decided on grounds unrelated to economic growth in the 2000s (see Section 3.3) and that the availability for conversion is driven by military redundancy rather than local economic demand. There are 46 former military airports, 9 of which opened after 2000. If the location and opening of these airports was truly unrelated to pre-existing economic conditions, then this instrument does not require that we focus in our incidentally treated group or control extensively for geographical fixed effects. In column 1 and 2 the instrument is the change in distance from a county to the nearest airport that was formerly in military use. This change occurs when a military airport converts to civil use. Column 1 and 2 use the full sample, column 3 and 4 the incidentally treated sample with nearest pre-existing airport fixed effects. The first stage in both columns is strong, with an F-statistic of over 50. The estimated elasticity is now 0.5 in the full sample and 0.65 in the incidentally treated sample, considerably larger than our main estimates. The point estimates are still large at around 0.4 when control variables are added in columns 2 and 4, though less precisely measured. Recall though, that we are only identifying effects from the opening of 9 new airports, so, if treatment effects are heterogeneous, this estimate may be less representative than our main estimates (i.e. our estimates are all Local Average Treatment Effects, Imbens and Angrist 1994).

5.4 Heterogeneity

There is marked heterogeneity response across a range of industry and county characteristics. Table 9 presents these results. The regressions are estimated by interacting our usual air market access index with an indicator that splits the sample in some way. Column 1 shows differences across industry groups – manufacturing (the baseline), and mining-energy-water related industries (row 2). The coefficient in the baseline manufacturing group is similar to our main estimates. The point estimates indicate smaller effects in the mining and power sectors – which seem intuitive given these sectors will not likely benefit from reductions in air freight costs, although they may still benefit from other forms of agglomeration economy arising from business travel and interactions. The difference is not, however, statistically significant. Neither do we find any difference according to capital intensity (column 2). There is much more marked heterogeneity in terms of firm size, as measured by above/below median employment in the county-industry group in the initial year of each period. It is the industries and counties with relatively small firms (average 118 employees) which benefit more than large firms (average 455) from market access improvements (column 3). Similarly, industry-county groups with a higher private sector capital share (i.e. not state owned) gain the most (column 4). Surprisingly, we find no evidence of positive complementarities between air market access and higher-skills (column 5) which counts against a story of these effects being driven by information sharing and face to face interaction amongst high skill groups (a common channel proposed for transport-related agglomeration economies), although there are positive interactions with population density, suggesting that most of these gains are accruing to firms in cities.

5.5 Air-side versus land-side access

In the final part of the empirical analysis, we turn to the decomposition of air market access into air-side and land-side components, as set out in equation (3). The results of this decomposition are in Table 10, where we show the results for gross industrial output and value-added (ASIF data), and GDP, by sector (from the county statistical year book data). The first rows shows the coefficients related to land-side distance reductions. These are in line with the results presented on overall air market access so far: positive and significant for industrial output, value added, secondary GDP and overall GDP, but zero in the primary and tertiary sectors. Clearly, it is land-side access changes that make the main contribution to the overall effects.

Results on air-side access present a much more mixed picture. Note the magnitude of the air-side coefficients is very large, because the standard deviation of the air-side market access changes over space is less than 10% of that attributable to land-side changes – see Table 1 and Figure 3. To make the effect sizes of these air-side and land-side changes more comparable it makes sense to multiply the coefficients by the standard deviations of the air access variables to give the effects related the change in air access change induced by new airports over this period. These numbers are shown as the effect sizes in square brackets in each column.

In columns 1 and 2, estimated on the county-by-industry panel, the coefficients are large and negative, although not statistically significantly different from zero. In column 3, we estimate from the ASIF panel, but aggregating to counties, such that we no longer control for industry specific fixed effects and trends. Removing the industry fixed effects in this way leads to positive coefficients on air-side access, similar in effect size to the land-side effects, although again these are not significant. Evidently the negative coefficients in columns 1 and 2 are specific to the within-industry changes; once we allow for effects from changes in the industry composition of counties over time, the effects of air-side access are positive but imprecisely measured.

Column 4 looks at the effects on overall GDP from the county statistical yearbook data. Air-side changes in access have very large positive and significant impacts on overall GDP – around size times larger than land-side in terms of effects sizes. The remaining columns look back at sector-specific GDP to try to understand where this result comes from. Column 5 switches to secondary GDP from the county statistical yearbook data, and gives very similar results to the ASIF data without industry controls (column 3). In columns 6 and 7 we see that the large coefficients on air-side access revealed in the overall GDP changes are due to large though non-significant changes within the services and agricultural/forestry sectors. This finding suggests that the availability of potential destinations, once a local airport is reached, has a much bigger role to play in these sectors. Another explanation is that our ASIF data covers only large firms, while the GDP figures relate to all firm sizes, suggesting that small firms may be more responsive. This is a possibility we are unable to pursue further given the data currently available for China.

6. Conclusion

We show evidence that the rapid expansion of the air transport network in China over the 2000s led to substantial growth in county-level industrial output and Gross Domestic Product. The estimates are based on a novel estimation approach that focuses on 'incidentally' affected counties, whose location midway between existing and new airports implies they not were explicitly targeted for development nor directly affected by airport operations. Our measure of treatment is an index of population or market access, which we decompose into air and land-side components. An instrumental variable strategy based on military airport locations supports our main findings.

We reach three main conclusions. First, improved market access due to land-side distance reductions leads to higher industrial output and GDP, with an elasticity of around 0.25. This effect is seen when using data from a survey of large industrial firms, and borne out by administrative data on county GDP and secondary sector GDP. Second, the main gains to manufacturing come from the land side cost reductions, highlighting an obvious but previously overlooked point that the accessibility of airports on the land side is the key factor that should guide airport location decisions. We do detect large effects from air-side availability of destination airports on overall GDP, although this is imprecisely measured in individual sectors. Third, though we find a positive effect on manufacturing and the wider industrial sector, we find no clear effects in the service sector, which runs counter to common assumptions about the role of air transport in business dealings in finance and other services in developed countries, and previous evidence for the historical US (Sheard 2014, Airports Commission 2015).

Based on this evidence, airport construction policy in China appears to have been successful in boosting local growth in the manufacturing sector. Extrapolating our estimates to the national level, the 35% increase in market access generated by airport network expansion over our study period implies and 8% increase in industrial output. The overall gain in industrial output in this period was 210%, so airports could explain a small but non-trivial proportion of aggregate growth. Of course, some of the increases we observe may represent displacement and sorting of activity between high and low access places, although our estimates are based on within-industry changes, are conditional on employment and capital inputs, and we see no corresponding changes in employment. These facts suggest that our findings are more likely attributable to micro-level productivity improvements. The implication is that air transport infrastructure has an important role to play in developing economies, such as China, where distances are vast and manufacturing plays a dominant role.

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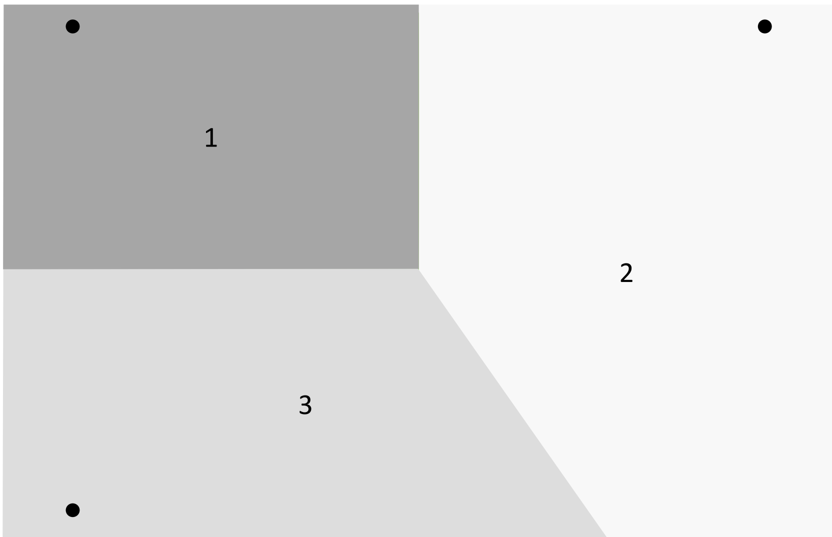
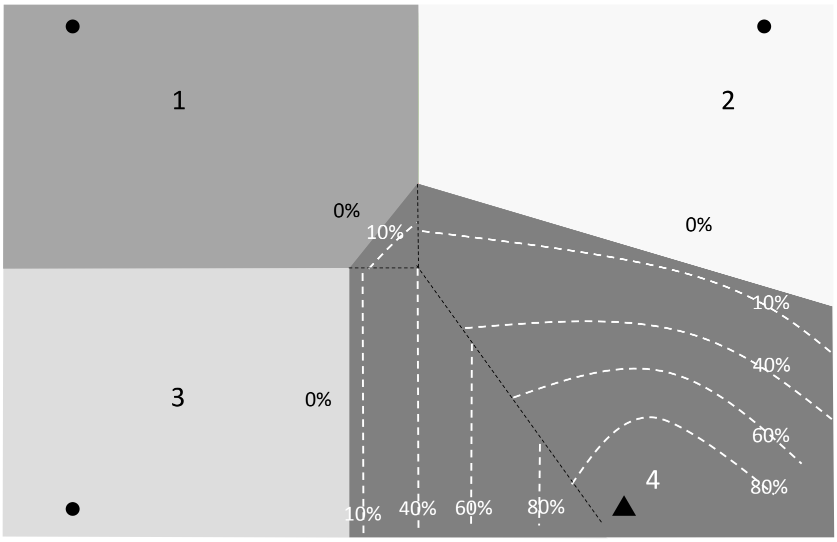
Figure 1: Schematic representation of changes in nearest-airport areas

Panel A: Catchment areas of 3 existing airports, assuming nearest airport chosen.



Panel A: Land areas nearest to each of 4 airports after construction of new airport 4. Market access changes: Air-side changes in catchment 1; Air-side changes in catchment 2; Air-side changes in catchment 3; New air side access from airport 4 and landside changes due to reductions in distance to airport for places formerly closer to airports 1,2 and 3. Figures in % show illustrative % distance reductions to nearest airport.



Panel A: Buffer zone around mid-way lines between each airport excludes places close to old and new airports. Example illustrated approximately for absolute difference in distance <60%.

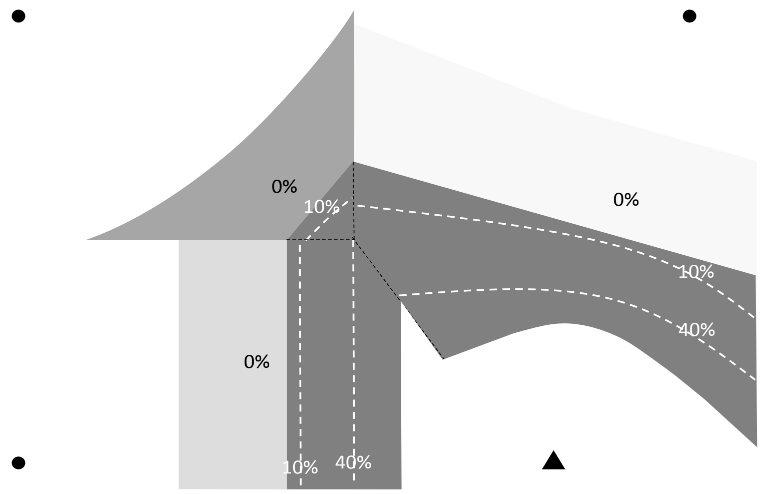


Figure 2: Airports in China opening 2002-2009

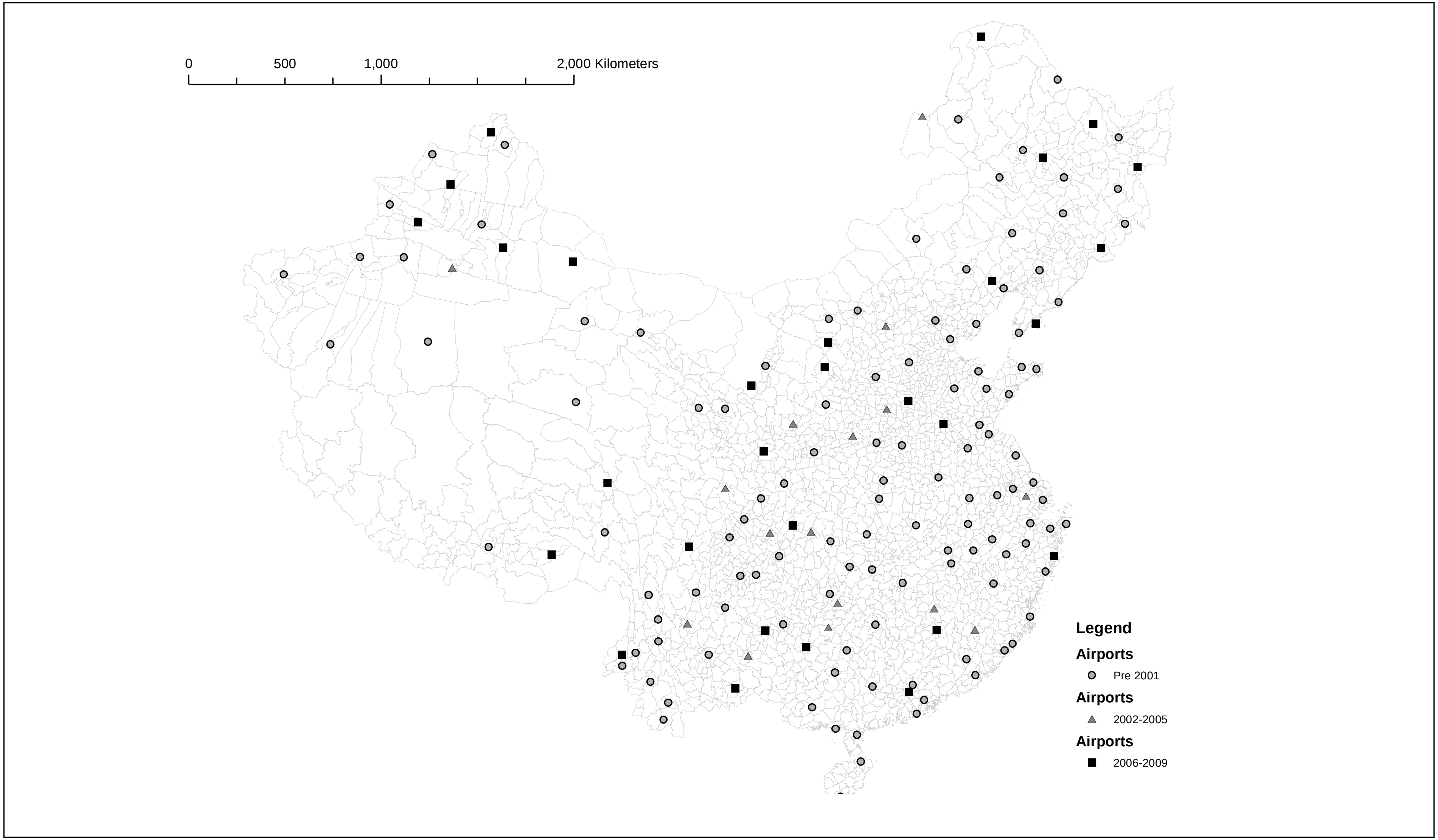


Figure 3: Air transport population access changes, 2002-2009

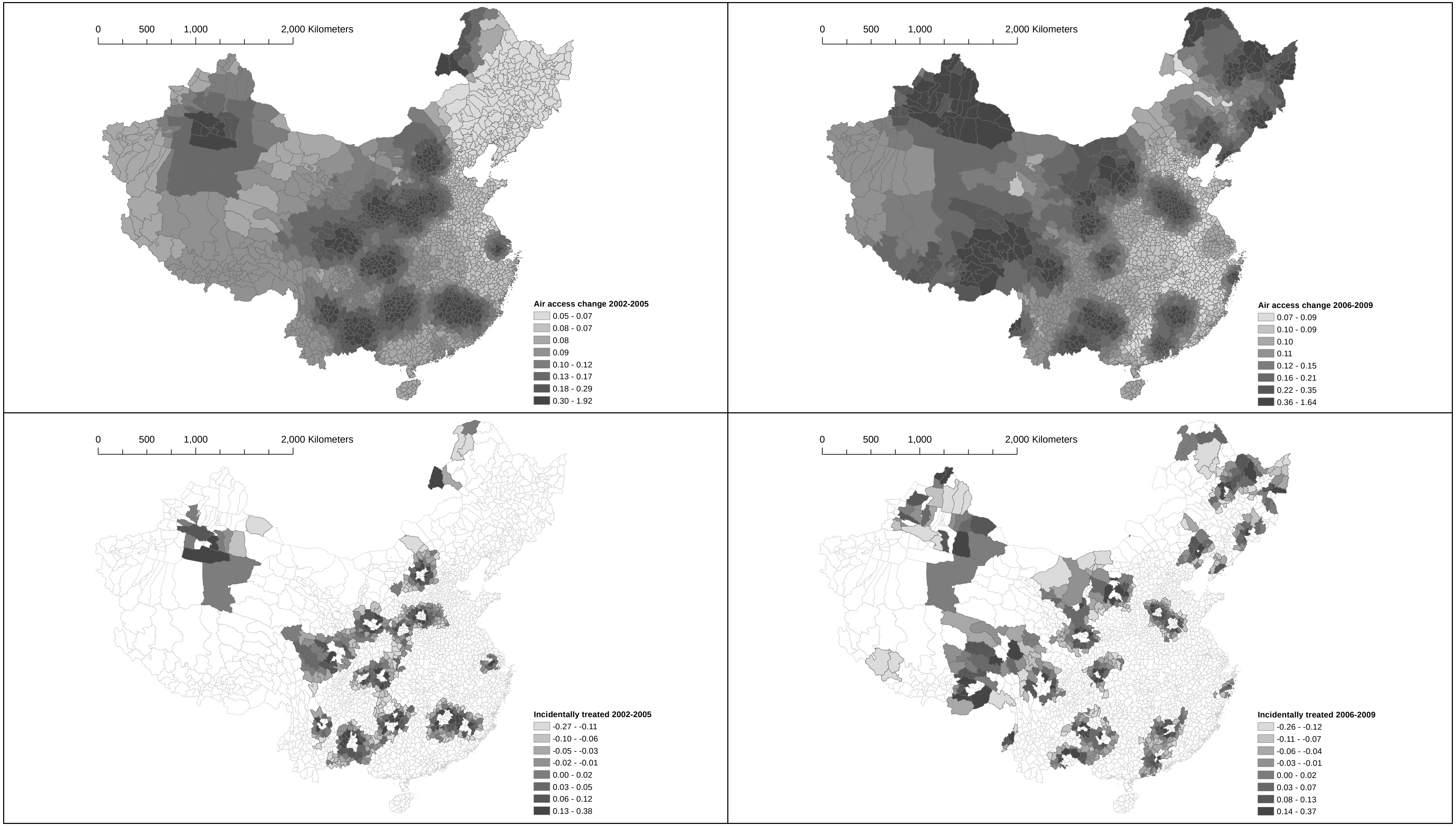


Figure 4: Air-side and land-side air transport population access changes, 2006-2009

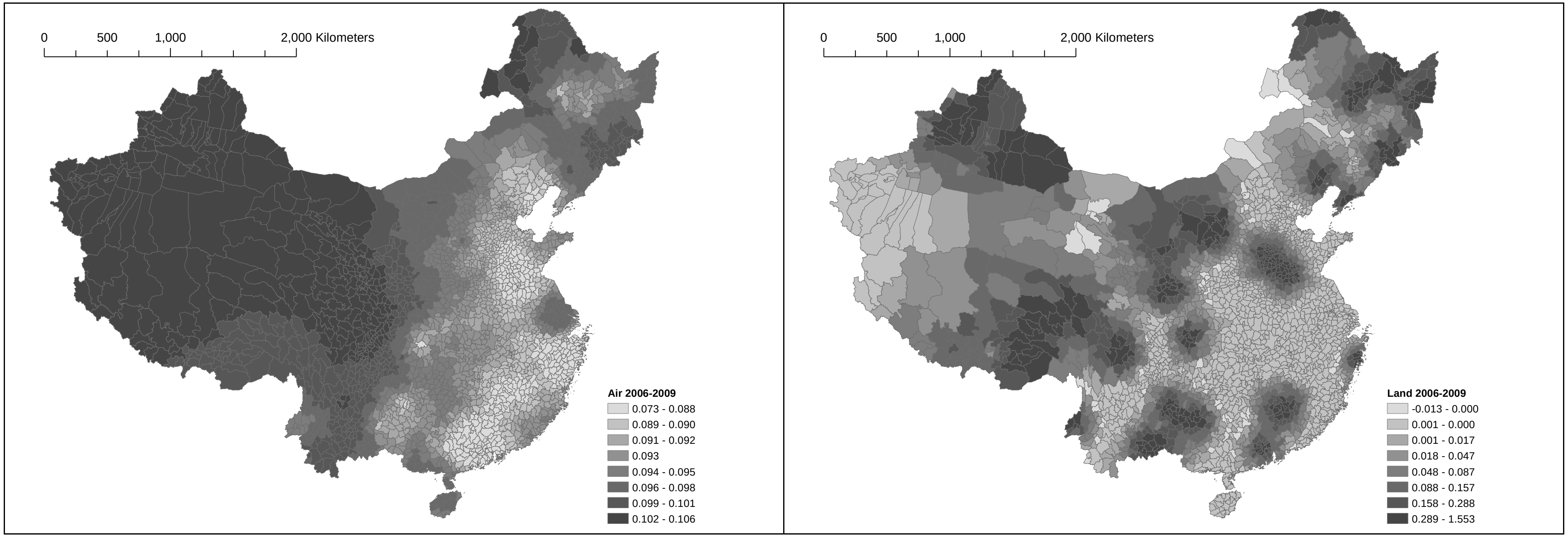


Table 1: Summary statistics for county and industrial data

Industrial data, 2001-2005, 2005-2009	Full N = 43906				Restricted N = 6904			
2-digit industry x county x period cells.	mean	sd	min	max	mean	sd	min	max
Air pop access first period (ln)	18.482	0.484	15.958	20.847	18.104	0.338	16.51	19.045
Change in ln air pop access (nearest 5 airp.)	0.151	0.182	0.047	1.9	0.31	0.138	0.052	0.81
Change in ln air pop access (at nearest 1)	0.158	0.312	0.046	3.135	0.312	0.291	0.053	1.177
Change in ln land-side air access	0.075	0.179	-0.014	1.839	0.229	0.136	-0.006	0.711
Change in ln air-side air acces	0.076	0.015	0.047	0.104	0.08	0.012	0.057	0.103
Distance to nearest airport start year	82.677	49.85	6.112	558.622	134.047	49.099	35.36	406.244
Distance to nearest airport end year	75.212	43.078	6.112	558.622	107.915	42.488	32.526	406.244
Distance to nearest new airport in period	351.028	288.156	8.136	2149.284	126.88	57.718	32.526	608.934
Gross output in start year (ln)	10.114	1.363	1.386	18.19	9.958	1.441	1.386	15.771
Change in ln gross output	0.566	0.986	-10.404	9.511	0.653	0.986	-6.087	9.511
Population (2000 census)	7.73E+05	7.28E+05	9201	8.31E+06	5.80E+05	3.48E+05	10890	2.00E+06
Share with high school education	0.25	0.293	0.007	2.38	0.217	0.291	0.016	1.597
County data, 2002-2006, 2006-2010	Full N = 4160				Restricted N = 976			
County x period cells.	mean	sd	min	max	mean	sd	min	max
Air pop access first period (ln)	18.25	0.576	15.851	20.875	17.947	0.411	16.053	19.045
Change in ln air pop access (nearest 5 airp.)	0.178	0.184	0.05	1.917	0.303	0.135	0.063	0.816
Change in ln air pop access (at nearest 1)	0.186	0.324	0.054	3.145	0.302	0.28	0.054	1.173
Change in ln land-side air access	0.095	0.183	-0.015	1.848	0.218	0.133	-0.013	0.711
Change in ln air-side air acces	0.084	0.012	0.056	0.106	0.085	0.012	0.056	0.106
Distance to nearest airport start year	107.662	71.236	6.112	742.021	153.247	65.998	22.782	703.681
Distance to nearest airport end year	97.176	65.816	6.112	742.021	126.492	61.899	22.075	703.681
Distance to nearest new airport in period	300.318	218.751	8.136	1481.069	150.358	86.043	30.061	1038.917
GDP start year (ln)	12.511	1.341	8.606	17.878	12.084	1.258	8.606	17.849
Change in ln GDP	0.651	0.28	-1.865	3.174	0.686	0.274	-0.735	2.095
Population (2000 census)	5.15E+05	5.15E+05	6384	8.31E+06	4.00E+05	3.57E+05	9699	6.18E+06
Secondary sector GDP share	0.431	0.165	0.05	2.931	0.419	0.177	0.057	0.885
Tertiary sector GDP share	0.344	0.119	0.022	4.403	0.339	0.105	0.083	0.838
Share with high school education	0.164	0.221	0.007	2.368	0.135	0.174	0.008	1.597

Notes: Unweighted summary statistics. Changes refer to 4 year changes. Restricted geographical subset is counties for which absolute value of difference between nearest airport distance at beginning of period and distance to new airports constructed during time period is less than 60% of the distance at beginning of period.

Table 2: Balancing on initial census characteristics and trends. Pre-treatment variables on changes in log air population access, 2000-2009.

	(1) Employment/ adult pop.	(2) Employment agriculture	(3) Employment mining	(4) Employment manufacturing	(5) Employment power	(6) Employment construction	(7) Employment tertiary	(8) Population 2000
Full sample								
Air transport	0.0188	0.1467*	0.6855**	-0.5981***	0.0067	-0.5191***	-0.1849*	-0.5046***
population access	(0.0204)	(0.0851)	(0.2718)	(0.1728)	(0.1267)	(0.1626)	(0.0974)	(0.1761)
Observations	2,372	2,372	2,295	2,355	2,357	2,338	2,372	2,373
R2	0.0015	0.0037	0.0105	0.0199	0.0000	0.0162	0.0068	0.0183
Incidentally treated								
Air transport	0.0127	-0.1340	0.0372	-0.1081	-0.1553	-0.0076	-0.1252	0.1236
population access	(0.0169)	(0.0914)	(0.3185)	(0.1728)	(0.1476)	(0.1765)	(0.0892)	(0.1587)
Observations	800	800	770	792	793	786	800	800
R2	0.4926	0.3164	0.3286	0.5224	0.3071	0.3798	0.4749	0.6461

	(9) Share pop over 15/16	(10) High school educated	(11) Unemployed	(12) 1990-2000 pop. change	(13) 1990-2000 chg. high sch.	(14) Elevation	(15) Precipitation	(16) Temperature
Full sample								
Air transport	0.0027	-0.1608**	-0.0650	0.0623**	-0.5160***	0.6035***	-0.1117*	-0.1520***
population access	(0.0314)	(0.0795)	(0.0602)	(0.0270)	(0.1831)	(0.1445)	(0.0645)	(0.0578)
Observations	2,371	2,372	2,372	2,273	2,258	2,112	2,117	1,998
R2	0.0000	0.0059	0.0022	0.0039	0.0184	0.0103	0.0019	0.0031
Incidentally treated								
Air transport	-0.0210	-0.0751	-0.0799	0.0949	0.1705	-0.1864	-0.0696	-0.0519
population access	(0.0156)	(0.0773)	(0.0535)	(0.0669)	(0.1674)	(0.2382)	(0.0972)	(0.0990)
Observations	800	800	800	768	760	796	798	741
R2	0.5287	0.5420	0.5409	0.0882	0.6094	0.2037	0.1451	0.1645

Table reports coefficients and standard errors from regression of county characteristics on 2009-2000 changes in air transport population access. Air transport population access is sum of inverse travel time weighted census 2000 county populations. All dependent variables in logs. Columns 2-7 are log shares of employment. Columns 10-12 are log shares of adult population. Standard errors clustered on nearest airport (~ 125). Incidentally treated geographical subset is subset of counties for which absolute value of difference between nearest airport distance at beginning of period (2000) and distance to new airports constructed during time period (2000-2006)is less than 60% of the distance at beginning. Regressions in incidentally affected group include controls for initial nearest airport fixed effects based on year 2000 airports (~89).

Table 3: Regressions of 4-year changes in industrial firm log gross output on 4-year changes in log air population access, 2001-2005-2009

Geographical subset	(1) Gross output Full sample	(2) Gross output Full sample	(3) Gross output Incidentally treated	(4) Gross output Incidentally treated	(5) Gross output Incidentally treated	(6) Gross output Incidentally treated	(7) Gross output Incidentally treated
Air transport population access	0.0512 (0.0620)	0.0534 (0.0377)	0.2582** (0.1010)	0.2591** (0.1031)	0.2612** (0.1007)	0.2838*** (0.0976)	0.2109** (0.0944)
Observations	43,906	43,906	6,904	6,904	6,904	6,771	6,904
R2	0.4467	0.4720	0.4562	0.4562	0.4606	0.4597	0.4624
Production input controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	2-digit	2 digit	2 digit	2 digit	2 digit	2 digit	2-digit
Nearest 2000 airport trends	No	Yes	Yes	Yes	Yes	Yes	Yes
Initial access trends	No	No	No	Yes	Yes	Yes	Yes
Additional controls	-	-	-	-	Census and geographic	Pre-2000 population trend dummies	Province dummies

Table reports coefficients and standard errors from regression of 2009-2005 and 2005-2001 changes in in log firm gross output on 2008-2004 and 2004-2000 changes in air transport population access. Air transport population access is sum of inverse travel time weighted census 2000 county populations. Travel times imputed as described in text. Data from Annual Survey of Industrial Firms 2001, 2005 and 2009, aggregated to county or 2-digit industry-by-county cells. Standard errors clustered on nearest airport (~ 106 clusters). All regressions include controls for firm log employment, log employment squared, log fixed assets, log fixed assets squared and log employment × log assets. All regressions include controls for initial nearest airport × time period fixed, effects based on year 2000 airports (~222 in full sample, ~107 in restricted sample). Lagged access is air population access in the first year of each period. Census and geographic controls are: 2000 census proportion high school educated proportion unemployed, proportion disabled; minority ethnic county dummy; dryness, days above 10°C, mean temperature, elevation, precipitation, straight line distance to coast, distance to provincial capital, distance to national border, urban district dummy. Pre-2000 population trend dummies are for 40 quantiles of the distribution of the 1990-2000 census change in population. Province dummies: dummies for each Chinese province (up to 31 in restricted sample). Incidentally treated geographical subset is subset of counties for which absolute value of difference between nearest airport distance at beginning of period (2000, 2004) and distance to new airports constructed during time period (2000-2004 or 2004-2008) is less than 60% of the distance at beginning of period. Gross output is nominal. Values deflated using province-year consumer price indices yield almost identical results.

Table 4: Regressions of 6-year changes in industrial log productivity measures on 6-year changes in log air population access, 2001-2007

Geographical subset	(1) Value-added Incidentally treated	(2) Value-added Incidentally treated	(3) Value-added Incidentally treated	(4) Value-added Incidentally treated	(5) Wages Incidentally treated	(6) Wages Incidentally treated	(7) Wages Incidentally treated	(8) Wages Incidentally treated
Air transport population access	0.3036** (0.1453)	0.2561 (0.1849)	0.3079* (0.1607)	0.2479 (0.1536)	0.0037 (0.1411)	0.0215 (0.1405)	-0.0557 (0.1288)	-0.0403 (0.1287)
Observations	3,965	3,965	3,884	3,965	4,037	4,037	3,953	4,037
R2	0.4603	0.4658	0.4625	0.4709	0.1376	0.1513	0.1585	0.1527
Production input controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	2 digit	2 digit	2 digit	2-digit	2 digit	2 digit	2 digit	2-digit
Nearest 2000 airport trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial access trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	-	Census and geographic	Pre-2000 population trend dummies	Province dummies	-	Census and geographic	Pre-2000 population trend dummies	Province dummies

Table reports coefficients and standard errors from regression of 2007-2001 changes in in log firm gross output on 2006-2000 changes in air transport population access. Air transport population access is sum of inverse travel time weighted census 2000 county populations. Travel times imputed as described in text. Data from Annual Survey of Industrial Firms 2007 and 2001, aggregated to county or 2-digit industry-by-county cells. Standard errors clustered on nearest airport (~ 77 clusters). All regressions include controls for firm log employment, log employment squared, log fixed assets, log fixed assets squared and log employment × log assets. All regressions include controls for initial nearest airport fixed effects based on year 2000 airports (~57)). Lagged access is air population access in the first year of each period. Census and geographic controls are: 2000 census proportion high school educated proportion unemployed, proportion disabled; minority ethnic county dummy; dryness, days above 10°C, mean temperature, elevation, precipitation, straight line distance to coast, distance to provincial capital, distance to national border, urban district dummy. Pre-2000 population trend dummies are for 40 quantiles of the distribution of the 1990-2000 census change in population. Province dummies: dummies for each Chinese province (up to 23 in restricted sample). Incidentally treated geographical subset is subset of counties for which absolute value of difference between nearest airport distance at beginning of period (2000) and distance to new airports constructed during time period (2000-2006) is less than 60% of the distance at beginning of period. Value-added and wages are nominal. Values deflated using province-year specific consumer price indices yield almost identical results.

Table 5: Regressions of 4-year changes in county outcomes on 4-year changes in log air population access, county yearbook data 2002-2006-2010

Geographical subset	(1) Urban employ. Incidentally treated	(2) Rural employ. Incidentally treated	(3) Urban income Incidentally treated	(4) Consump. Incidentally treated	(5) GDP Incidentally treated	(6) GDP primary Incidentally treated	(7) GDP secondary Incidentally treated	(8) GDP tertiary Incidentally treated	(9) Fixed asset investment Incidentally treated	(10) Local govt exp. Incidentally treated
Air transport population access	0.0168 (0.1746)	0.0696 (0.0679)	-0.0142 (0.1330)	0.0189 (0.0859)	0.1918** (0.0911)	-0.0032 (0.0790)	0.4164** (0.1649)	0.0007 (0.1291)	0.5949*** (0.1705)	0.0840 (0.0690)
Observations	813	738	869	944	976	919	919	530	855	976
R2	0.4038	0.2143	0.4834	0.2799	0.3813	0.3959	0.2861	0.3620	0.2815	0.5398
Initial airport	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial access	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table reports coefficients and standard errors from regression of 2010-2006 and 2006-2002 changes in outcomes on 2009-2005 and 2005-2001 changes in air transport population access. Air transport population access is sum of inverse travel time weighted census 2000 county populations. Travel times imputed as described in text. Data from county statistical yearbooks. Standard errors clustered on nearest airport (~125 clusters). All regressions include controls for initial nearest airport × time period fixed, effects based on year 2000 airports (~125-130 categories). Lagged access is air population access in the first year of each period. Incidentally treated geographical subset is subset of counties for which absolute value of difference between nearest airport distance at beginning of period (2001, 2005) and distance to new airports constructed during time period (2001-2005 or 2005-2009) is less than 60% of the distance at beginning of period. Monetary variables are nominal. Values deflated using province-year specific consumer price indices yield almost identical results. Note, sample sizes vary due to missing county data. Tertiary GDP only available for limited number of counties in 2002, hence lower number of observations.

Table 6: Robustness tests, industrial firm data, 2001-2005-2009

Geographical subset or specification	(1) Gross output 60% buffer	(2) Gross output 50% buffer	(3) Gross output 40% buffer	(4) Gross output 70% buffer	(5) Gross output Include nearest new airport dummies	(6) Gross output Drop counties with high speed rail lines
Air transport population access	0.2591**	0.2953**	0.2811	0.1565*	0.2628***	0.2524**
	(0.1031)	(0.1372)	(0.1939)	(0.0886)	(0.0869)	(0.1082)
Observations	6,904	5,686	4,318	7,782	6,904	5,752
R2	0.4562	0.4638	0.4644	0.4552	0.4616	0.4508
Geographical subset or specification	(7) Gross output Minimum 100k to airports	(8) Gross output Min. 100km Max 200km to airports	(9) Gross output Trim top and bottom 5% access change	(10) Gross output Trim top and bottom 5% change in gross output	(11) Gross output 1st Period 2001-2005	(12) Gross output 1st Period 2005-2009
Air transport population access	0.3956**	0.3693*	0.3762***	0.1620**	0.1924	0.3494***
	(0.1860)	(0.2041)	(0.1115)	(0.0782)	(0.1789)	(0.1051)
Observations	3,924	3,741	6,207	6,236	3,310	3,594
R2	0.4629	0.4718	0.4599	0.3489	0.4161	0.5292
Production controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	2 digit	2 digit	2 digit	2 digit	2 digit	2 digit
Nearest 2000 airport	Yes	Yes	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes	Yes	Yes

Notes as Table 3.

Table 7: Alternative air access treatment

	(1) Gross output Change in nearest airport ln distance	(2) Gross output Change in nearest airport ln distance – airports proposed 2010-2020	(3) Gross output Population air access, nearest airport	(4) Gross output Non population weighted centrality	(5) Gross output Modified speed assumptions
Geographical subset	Incidentally treated	Incidentally treated	Incidentally treated	Incidentally treated	Incidentally treated
Air transport access	-0.1104** (0.0446)	-0.1078** (0.0452)	0.0950** (0.0423)	0.2563** (0.1041)	0.2618** (0.1025)
Future air access	- -	0.0157 (0.0251)	- -	- -	- -
Observations	6,904	6,904	6,904	6,904	6,904
R2	0.4562	0.4562	0.4561	0.4562	0.4563
Industry fixed effects	2-digit	2-digit	2-digit	2-digit	2-digit
Initial airports	Yes	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes	Yes

Table reports coefficients and standard errors from regression of changes in outcomes on changes in air transport population access. Speeds in column 4 changed to 600km/h fair speed, 75km road speed, 1.5 hr embark/disembark time, minimum 30 minute flight time. For further notes see Table 3.

Table 8: Instrumental variables estimates

	(1) Gross output Military conversion IV	(2) Gross output Military conversion IV	(3) Gross output Military conversion IV	(4) Gross output Military conversion IV
Geographical subset	Full sample	Full sample	Incidentally treated	Incidentally treated
Air transport access	0.5060*** (0.1361)	0.4102*** (0.1363)	0.6537* (0.3816)	0.4268 (0.3360)
First stage	-0.2739*** (0.0352)	-0.1895*** (0.0256)	-0.1895*** (0.0256)	-0.1925*** (0.0263)
First stage F	60.06	57.68	54.61	53.38
Observations	43,906	43,906	6,904	6,904
Industry fixed effects	2-digit	2-digit	2-digit	2-digit
Initial airports	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes
Additional controls	-	Census and geographic	-	Census and geographic

Table reports coefficients and standard errors from regression of changes in outcomes on changes in air transport population access. 'Military conversion' instrument is change in distance to nearest airport converted to civil from military over the 2000-2004 or 2004-2009 periods. See Table 3 for further notes.

Table 9: Heterogeneity by county-industry characteristics

	(1) Gross output × Extraction and power	(2) Gross output × Large firms	(3) Gross output × High K/L	(4) Gross output × High state capital share	(5) Gross output × High high-school share	(6) Gross output × High population density counties
Geographical subset	Incidentally treated	Incidentally treated	Incidentally treated	Incidentally treated	Incidentally treated	Incidentally treated
Air transport population access	0.2923** (0.1195)	0.2724** (0.1054)	0.4091*** (0.1173)	0.3540*** (0.1080)	0.3161*** (0.1125)	0.1568 (0.1088)
× Above median heading characteristic	-0.1237 (0.1605)	-0.0320 (0.0621)	-0.2739*** (0.0777)	-0.4613*** (0.0744)	-0.1637* (0.0952)	0.1817** (0.0742)
Observations	6,904	6,904	6,904	6,904	6,904	6,904
R2	0.4563	0.4563	0.4579	0.4589	0.4568	0.4569
Production inputs	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	2-digit	2-digit	2-digit	2-digit	2-digit	2-digit
Initial airports	Yes	Yes	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes	Yes	Yes

Table reports coefficients and standard errors from regression of changes in outcomes on changes in air transport population access. Splits are based on median values in base period (2001 or 2006) or 2000 for population census variables.

Table 10: Decomposition of air-side and land-side population access changes.

Geographical subset	(1) Gross output Incidentally treated	(2) Value-added Incidentally treated	(3) Gross output Incidentally treated	(4) GDP Incidentally treated	(5) Secondary GDP Incidentally treated	(6) Tertiary GDP Incidentally treated	(7) Primary GDP Incidentally treated
Land-side airport	0.2268**	0.2691*	0.3183*	0.2197**	0.4231**	0.0232	0.0208
access	(0.1071)	(0.1471)	(0.1787)	(0.0904)	(0.1676)	(0.1229)	(0.0801)
Effect size	[0.0313]	[0.0371]	[0.0439]	[0.0297]	[0.0584]	[0.0031]	[0.0028]
Air-side network access	-10.8398	-9.6502	4.1628	14.7935***	3.7998	8.7002	12.0738
	(7.3896)	(12.3606)	(7.9177)	(5.4337)	(10.2526)	(14.9004)	(8.7435)
Effect size	[-0.1300]	[-0.1158]	[0.0500]	[0.1775]	[0.0456]	[0.1044]	[0.1449]
Observations	6,904	3,965	847	976	919	530	919
R2	0.4566	0.4317	0.6458	0.3868	0.2862	0.3631	0.3991
Industry fixed effects	2-digit	2-digit	-	-	-	-	-
Initial airports	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table reports coefficients and standard errors from regression of changes in outcomes on changes in air transport population access. Air transport population access is sum of inverse travel time weighted census 2000 county populations. Travel times imputed as described in text. Data from Annual Survey of Industrial Firms (columns 1-3) and county statistical yearbooks (columns 4-5). Standard errors clustered on nearest airport. All regressions include controls for initial nearest airport × time period fixed, effects based on year 2000 airports. Lagged access is air population access in the first year of each period. Columns 1 and 2 include 2-digit industry fixed effects. Incidentally treated geographical subset is subset of counties for which absolute value of difference between nearest airport distance at beginning of period and distance to new airports constructed during time period is less than 60% of the distance at beginning of period. Note, tertiary GDP only available for limited number of counties in 2002, hence lower number of observations.

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