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Airports, access and local economic performance: evidence from China

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Abstract

In this article, we study the effect of airports on local economic performance that arises from better access to domestic markets in the context of China's recent airport network expansion. We measure access through the changes in network closeness centrality implied by the contraction in potential journey times between counties within China. Our key finding is that better access—primarily due to landside distance reductions to airports—increased manufacturing productivity. The analysis is carried out on a panel of counties built from micro data on industrial firms, administrative records and census data. To mitigate endogeneity issues, we focus on a subsample of 'incidentally' affected counties, whose location midway between existing and new airports implies that they were neither explicitly targeted for development nor directly affected by airport operations.

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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 is an obstacle to local economic development. In large developing economies

1 IATA (2014a, b); OECD International Transport Forum (2013).

with poorly established land transport, the time savings from expanding the airport network are clearly potentially large. The fixed costs of airports are also relatively low compared with road and rail infrastructure spanning large distances. 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, there have been airport 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. Some notable early exceptions include Brueckner (2003), Button et al. (1999) with more recent contributions from Redding et al. (2011), Giroux (2013), LeFors (2015), McGraw (2015), Sheard (2014, 2019), Blonigen and Cristea (2015) and Campante and Yanagizawa-Drott (2018).

This article is the first study to examine the economic impacts of new airports in a large developing country, focussing on the productivity gains 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. First, 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 Chinese yuan (RMB, 46 billion USD) spent constructing 38 new civil airports between 2006 and 2010 (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 was the world's second largest air transportation market, carrying 353 million passengers and moving 16 billion tonne kilometres of freight (compared with 743 million passengers and 37 billion tonne kilometres in the USA).[3] This rapid expansion means that there are many new airports and large changes in the geographical patterns of accessibility on which we can base our estimation.

Methodologically, estimation of the causal impacts of airports on economic performance faces serious challenges because places with and without airports will differ on many pre-existing dimensions and because airport construction might be coincident with other policies. Separating out the effects of the supply of airports from other determinants of economic performance is difficult.[4] Distinguishing the 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 on airport construction (though is a feature of work that looks at air links, such as Campante and Yanagizawa-Drott, 2018).

There are key elements of our research design, which push our contribution beyond what has been done before to tackle these issues. First, our treatment variable is a closeness centrality index which provides a continuous measure of population access.

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

3 Authors; own calculations from CAAC (2013) World Bank Development Indicators (2014), IATA (2014 a,b).

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 article.

This type of index is variously referred to in the literature as market potential, population potential, effective density, market access or closeness centrality, dating back to Harris (1954) and recently applied, for example, in Gibbons et al. (2019) and Donaldson and Hornbeck (2016). We refer to it here simply as air transport access. This air transport access index involves aggregating potential destinations using imputed minimum potential 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 airside linkages across China from one airport to another, and because they reduce the landside journey times from firms (or residents) to airports. In our main index, we use county populations as the destination node weights in this index. An important point is, however, that these destination weights are irrelevant and can be set to one—implying that it is the contraction in potential journey times between origin and destination counties that matters empirically, not what is at the destinations. A corollary of this observation is that the size of destination airports or whether they are international or not has no empirical relevance.

An innovation in our article 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 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, which 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: (i) 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 (ii) comparable neighbouring counties that remained closest to existing airports and so were less affected. Variation in changes in air transport access 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 pre-existing characteristics of the counties selected in this way are, we show, 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 the 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 'indirect' and 'induced impacts') and the impact of other transport infrastructure or other local policies that were put in place to support the airport development.

All this analysis is conducted on a unique bespoke panel dataset of counties—covering mainland counties and urban districts in China, constructed from micro data from the Annual Survey of Industrial Firms, statistical yearbooks, the population census and various other web and geographical sources.

Our key finding is that improvements in domestic air transport access generated increased local industrial productivity (gross output and value-added, conditional on employment and capital) and Gross Domestic Product (GDP). The impacts 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 our preferred index of access are around 0.2–0.3. The scale of this effect requires some interpretation. First, it is an 'intention to treat' effect, based on the construction of airports and the potential contraction in county–county origin–destination journey times, irrespective of whether air services were operated on these links. In terms of the impact of this airport expansion policy on relative county performance, one standard deviation in the distribution of access improvements across over a 4-year interval implies a 4.5% increase in productivity. If one is prepared to extrapolate to aggregate national changes, then this effect implies a gain in industrial output of around 8% from the average national access change of over the whole 2001–2009 period. 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 landside versus airside access suggest that these effects on the industrial sector are primarily due to reductions in the landside distance from counties to airports. The estimated effects of airside availability of potential destination airports are less well determined although we find large positive effects on GDP.

The structure of the article 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 literature

Transport infrastructure such as roads, railroads and airports affects local economic activity through at least two theoretical channels. 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. Improved transport also gives rise to agglomeration economies 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 (Lovely et al., 2005; Bel and Fageda, 2008; Redding and Turner, 2015).

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., 2019) and in developing economies including China (Banerjee et al., 2012; Zheng and Kahn, 2013; Faber, 2014; Baum-Snow et al., 2017; Qin, 2017). In contrast, the literature on airports is so far mainly limited to developed countries, particularly the USA. Dealing with the endogeneity of airport location is the major challenge. A popular method is to estimate the effect of hub airports, either directly or as predictors of airline traffic, on the debatable assumption that the location of hubs is unrelated to other factors that might influence local growth (Button et al., 1999; Brueckner, 2003; Green, 2007; Percoco, 2010). 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, the limitation being the assumption that historical instruments have no direct effects on future economic outcomes (Sheard 2014). Other methods and instruments have been tried, predicting local airport traffic growth from national trends (Sheard, 2019), attributing changes in air traffic to specific airline deregulation events (Blonigen and Cristea, 2015) and exploiting discontinuities in air travel times at long inter-city distances, caused by regulatory constraints on flight staff working time (Campante and Yanagizawa-Drott, 2018). Generally, these studies find some impact on population or employment, at least in some sectors.

None of the existing literature can tell us much about the local productivity impact of transport cost reductions from building of domestic airports in a developing country.[5] Few studies explicitly exploit the opening of new airports to estimate their impact on local economic outcomes, in a difference-in-difference design. The only example of which we are aware is Tveter (2017) who looks at regional airport development in Norway, finding positive but insignificant effects from new airports on local employment and population. Moreover, previous work looks only at the impact on the employment and incomes of the cities or regions in which airports are located, sometimes with extensions to look at spillovers (Percoco, 2010) or to estimate multiplier effects (Sheard, 2019). Few try to separate out to what extent the impacts are attributable to travel time reductions (or 'catalytic' impacts in the airport economic literature)—the main purpose of air transport. None of the existing work links airports to micro-level firm data on production. Our article offers contributions on these key 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

5 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 traffic (Jin et al., 2004; Yao and Yang, 2008).

typical in developed countries (OECD International Transport Forum, 2013) 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 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. While 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 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 (roads 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 no '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 (CAAC, 2008). 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. In the first phase up to 2011, 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 200 km 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 Models and empirical specification

The starting point for our empirical analysis is a panel fixed-effects production–function 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 productivity over this period. We implement this through a regression of long-time interval changes in outcomes—industrial output, value added and GDP—on the corresponding change in air accessibility for counties in mainland China:

$$\Delta\ln y_{it} = \alpha + \beta \cdot \Delta\ln \mathrm{air}_{it} + x_{it}'\gamma + \epsilon_{it} \tag{3.1}$$

where,$\Delta\log y_{it}$ denotes the change over time in the outcome variable up to year t, that is, $\Delta\ln y_{it} = \ln y_{it} - \ln y_{it-s}$, where s ranges between 4 and 9 depending on the data used. The treatment variable is $\Delta\ln \mathrm{air}_{it}$ and is the corresponding 1-year lagged change over time in the natural logarithm of air transport access within panel units of analysis i (we suppress the 1 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. We use a multiyear time interval in order to estimate the impact of the cumulative growth in the airport network over a number of years, rather than the impact of year-on-year changes. 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 (3.1) corresponds to a time-differenced aggregated production function at two-digit-by-county level. In this case, we control for changes in firm inputs (using a quadratic in ln employment and ln total assets that is a trans-log production function) plus two-digit industry dummies to allow for industry-specific time trends. Unobservables are represented as usual by ϵ_i.

The treatment variable $\Delta\ln \mathrm{air}_i$ is change in the log of an index of the expected air transport accessibility, given a county's geographical location in relation to existing and new airports. This index is based on a standard inverse-travel-time weighted closeness centrality index (or market access index) taking into account journey times between counties and has the following structure:

$$\mathrm{air}_{it} = \sum_{j\in J_{it}} \left(\sum_{k\in K_t} \mathrm{pop}_k \times \mathrm{airtime}_{jk}^{-1} \right)_j \times \mathrm{landtime}_{ij}^{-1} \tag{3.2}$$

First, we calculate centrality 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 access index 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 in our preferred specification. We use multiple airports in the potential set of origin airports for each county because, in many cases, counties will have many alternative airports at similar distances in different directions. Counties, while small in relation to China as a whole, are also quite large in area. For both reasons, it is impossible to infer which is the optimal airport choice of airport for a county and the concept is theoretically fuzzy since this might differ for different firms within a county. The index is, therefore, an index of expected air access given a county's location in relation to its nearest airports. We check robustness to the number of airports, and to other variants in the functional form of the index. Estimates derived from simple measures of the reduction in distance to the nearest airport yield qualitatively similar results. More detail on construction of this index is given in Section 4 and Appendix A.

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 between airports, 'Manhattan' distance ($1.41 \times$ distance) between counties and airports, adjusted for typical travel speeds and connection times, fixed over time (for details, see Appendix A). The population weights pop$_k$ from the 2000 population census are also fixed over time (and, as we will show, are somewhat irrelevant and can be set to a constant without changing the results). Therefore, the only variation over time in the air transport 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 (3.2), varies across space because it interacts with the set of nearest neighbour airports for each county. Different sets or airports in J_{it} have different distances to the global set of airportsK_t.

There are necessary approximations in this index. First, we do not consider access to countries outside of China; our analysis refers only to domestic travel. As we will show, the absence of information on international connections is irrelevant, when our interest is on domestic travel. The weights we place on airports make no difference to the estimates, so we would find nothing different if we were to assign some airports higher weights based on their having international connections. Secondly, we do not use actual airside travel times or available flight routes because (i) we do not have the information for the full set of airports for all periods and (ii) the choice of routes that are operated is potentially endogenous to demand and local economic performance. This means that our results should be interpreted as 'intention to treat' effects: the impact of the potential contraction of journey times between counties due to new airport infrastructure, averaging over counties where those services materialised and those where they did not. Flights are genuinely possible in principle from any airport to any other given the type of airports we consider (they are all capable of landing, for example, a Boeing 737). To check whether the lack of full information on the operated network is likely to have any material impact on our results, we compared the airport-level population-weighted centrality index based on the full set of airport–airport potential flights, with the airport-level population-weighted centrality index based on regular routes shown in CAAC data in 2010. The correlation between the centrality based on actual and potential networks is over 0.9 so it is unlikely that using actual network data would make much difference to the regression results, even if it was methodologically desirable. Thirdly, we do not use the actual land transportation network or travel times because: (i) we do not have historical information on the road network; (ii) land side travel speeds and infrastructure, and hence an index constructed using actual land travel times, are potentially endogenous to local economic performance; and (iii) as discussed above, counties can be large, we do not know the location of these firms within a county, therefore computing road network travel distances would be bogus in terms of any additional precision. In practice, using geographical rather than road-based times to airports is likely to be unimportant, since it is well known that in the cross-section, geographical and road network distances are highly correlated (Combes and Lafourcarde, 2005). Since we want to look at the effects of airports, holding the road network constant, there would be no gain from more accurate road travel time information. We do, however, check that our results are not affected contemporaneous highway and rail infrastructure development. Lastly, the destination population weights are the census populations in the counties in which the airports are located. In principle, we could add an additional step and aggregate neighbouring groups of destination counties back to destination airports using landside travel times to get airport-specific pop_a (as sometimes attempted with structural market access indices). However, this risks counting an origin county and its neighbours within its own external air transport access index, when origin and destination airports are moderately close together. To avoid this kind of problem, we restrict attention to airport-to-airport routes longer than 200 km (and 300 km in a robustness test). Fixed time costs are also included for check-in and disembarkation to down-weight the influence of short duration flight times on routes that are unlikely to be used in practice.

A useful feature of the structure 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 (3.2) as $\text{air}_{it} = A(K_t, J_{it})$ and the change $\Delta\ln \text{air}_{it} = \ln A(K_t, J_{it}) - \ln A(K_{t-s}, J_{it-s})$, we can by construction write:

$$\Delta\ln \text{air}_{it} = \{\ln A(K_t, J_{it}) - \ln A(K_t, J_{it-s})\} + \{\ln A(K_t, J_{it-s}) - \ln A(K_{t-s}, J_{it-s})\} \quad (3.3)$$

The first term on the right-hand side is the imputed landside change in access, which is the change 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 airside change in access, holding the set of local airports constant, but changing the availability of airports in the rest of China. These components can be included as separate regressors in (1) to estimate their separate contributions.

3.3 Identification issues

Ordinary least squares estimate of β in Equation (3.1) 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 air transport access is that new airport locations are endogenously determined. As usual in this type of fixed effects/difference-in-difference analysis, the key issues are: (i) initial conditions and pre-existing trends in economic performance between more and less treated counties and (ii) 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.

The first element in our identification strategy exploits random variation in changes in the air transport access index induced by the changing geometric relationship between counties and the set of existing airports and new airports in the index in different years [Equation (3.2)]. 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 their nearest new airports constructed over the time interval up to year (between $t - s$ and t). These zones comprise two groups of counties: (i) places that are largely unaffected in terms of landside transport costs by new local airport development because their existing nearest airport remains the closest, although they are affected by the airside network expansion and (ii) neighbouring counties who experience a reduction in distance to their nearest airport, so experience landside cost reductions plus airside gains.

The rationale for this focus is 3-fold. First, 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 (3.2)) 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 transport access (as in Equation (3.2)) occur due to changes in the set of nearest-neighbour airports (J_{it} in Equation (3.2)), and these changes occur randomly and discontinuously depending on a county's position relative to existing and new airports.[6]

To illustrate these points, Figure 1 shows a highly stylised example. Panel A shows the catchment areas of three 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 of 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 access even in this simple example are complex. Places still in the catchment areas of airports 1–3 experience no landside improvements because they remain closer to airports 1, 2 or 3 than airport 4. However, they experience airside 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 airside access too, but also experience a landside improvement 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 cut-off at 60% distance reduction) to ensure that places close to new airports and directly targeted or

6 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.

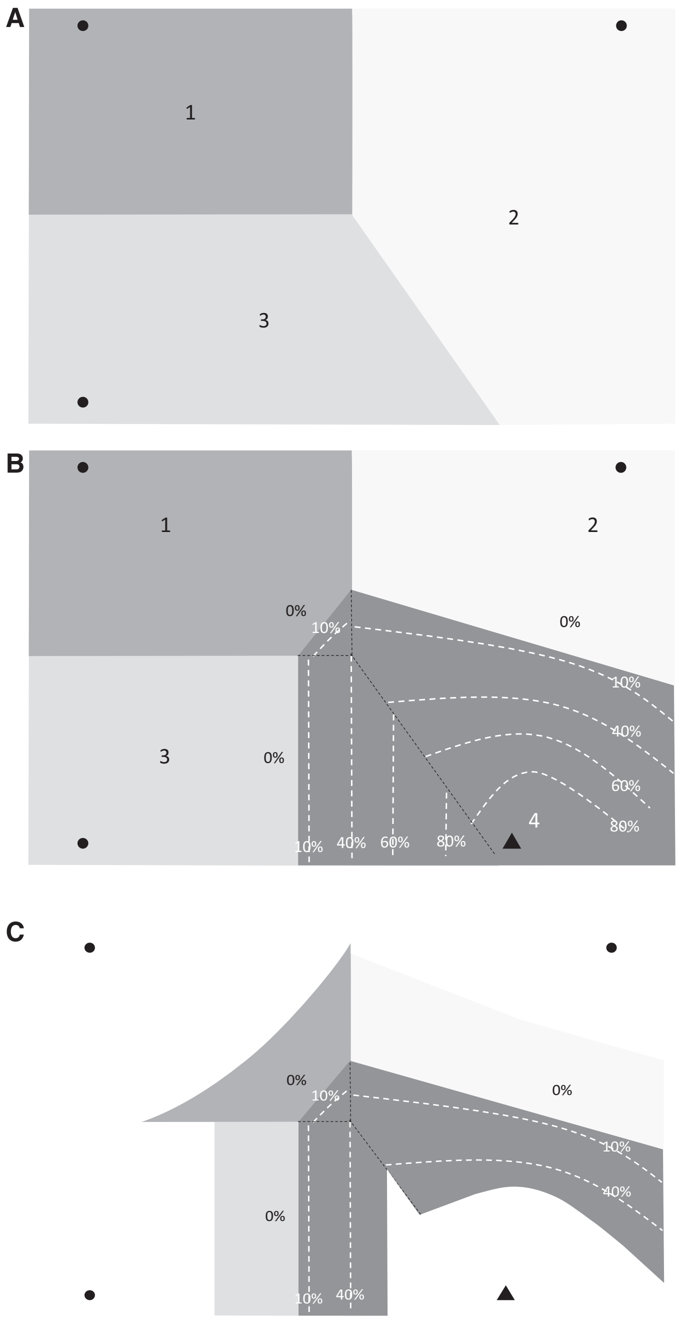

Figure 1. Schematic representation of changes in nearest-airport areas. (**A**) Catchment areas of three existing airports, assuming nearest airport chosen. (**B**) Landside access changes in catchment areas nearest to each of four airports after construction of new airport 4. Landside changes due to reductions in distance to airport for places formerly closer to airports 1, 2 and 3. Figures in percent show illustrative percentage landside distance reductions to nearest airport. Note all catchment areas experience airside access changes due to new airport 4. (**C**) 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%.

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. Note, we are not using two groups of counties—just treated and just untreated—as discrete treatment and control groups. Our treatment is a continuous index of air transport access, based on multiple local airports, which varies within the buffer zones defined as above. The intention is to select a sample of counties which are neither expressly targeted nor expressly non-targeted and to estimate from the incidental variation in the access changes within this group.[7]

4. Data

Our dataset is built up from a number of sources. The geographical unit of analysis is the county, based on 2004 boundaries, using geo-referenced county boundary data from the Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences. All geographical units are county-level administrative units except for: (i) urban districts administered by the four provincial-equivalent ranked municipalities, namely Beijing, Shanghai, Tian-jin and Chongqing, as they are directly governed by municipalities; (ii) former counties such as Dongwan that have been upgraded into (semi-) prefecture city administrative units; and (iii) 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 are discussed in Li et al. (2016). Our empirical specifications explore the results' sensitivity to alternative county sub-samples.

Our primary source for firm performance is micro data from the Annual Survey of Industrial Firms (ASIF) from 2001 to 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 (Zheng et al., 2015; Ding et al., 2016).[8] 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 and cannot estimate firm fixed effects regressions, but aggregate to county-by-industry-by-year cells using two-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

7 In effect, this is a spatial regression kink design. The rate of change of the accessibility gain, with respect to distance of a place from a new airport, changes at some threshold distance to that new airport. This threshold distance is determined by how far away the nearest existing airport is from the new one.

8 The industrial firm data are similar to the Longitudinal Research Database in the USA and the Annual Respondents Database in the UK.

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). We use data up to 2007 to look at value added which does not appear in the 2009 data.

As an alternative source, to cross-check our ASIF-based results, we extract GDP figures from the China Statistical Yearbooks for the Regional Economy (county level) for 2002–2010 and the China Economic and Social Development Statistical Database. These GDP figures cover all of mainland China, and our dataset improves on previous county datasets which had incomplete geographical coverage (and provides immensely more geographical detail than the prefecture or province-level data commonly used). 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, 2017) suggest that GDP figures at the local level are of high quality.

Additional data include variables from the 1990 and 2000 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 Centre 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[9] with regular commercial flights open by the end of 2010 form the basis for our air transport 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 transport access index in Equation (3.2) 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. The details of how we construct the index is described in Appendix A. These data sources and air transport 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 transport access measures for 2000, 2004 and 2008. This estimation dataset allows to look at the effects of the air network expansion from 2000 to 2008 on the performance of large industrial firms from 2001 to 2009, in two 4-year intervals. To look at value-added, 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 transport access indicators from 2001, 2005 and 2009, allowing us to look at changes in outcomes in two 4-year intervals from 2002 to 2010. Lastly, we join data on changes in the air transport access indices between 2000 and 2009 to census data from 2000 and on the changes in census population between 1990 and 2000 in

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

order to check for correlation between air transport access changes and pre-existing county characteristics and trends.

5. Results

5.1 Maps and descriptive statistics

We look first at the patterns of air transport access changes. Figure 2 shows the distribution of airports across the study area,[10] 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 in later periods 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 transport access index changes over these two periods, where the index is constructed from county populations, imputed airport–airport flight times and imputed county–airport land travel times as described in Sections 3.2 and 4. 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 access index changes shown are the residuals from a regression of the index changes shown 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 transport access on economic performance in our regressions: the variation in the index 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, our index of air transport access can be decomposed additively into airside and landside components. Figure 4 illustrates these separate components, for airports constructed from 2006 to 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 airside 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 landside accessibility changes.

10 Note that map figures in this paper only indicate the main study area, instead of the whole geographical boundary of China.

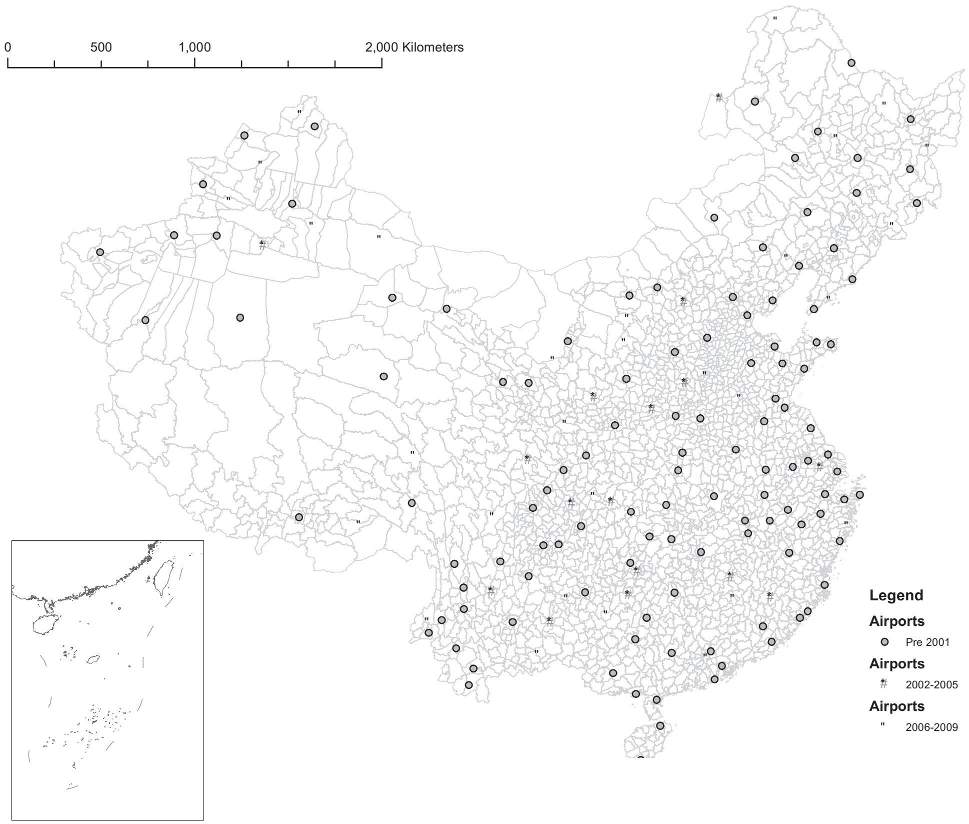

Figure 2. Airports in study area.

Table A1 summarises the key variables used in our analysis. Some key points to note are that there are 2387 counties in total, 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. Evidently, the incidentally treated group is not perfectly representative of China as a whole, having lower output, lower levels of education and smaller populations, although similar industrial structure. As with any quasi-experimental analysis, there is an inevitable trade-off here between the internal validity gained by this sample restriction and the potential generalisability to counties outside the sample.

Table 1 assesses one aspect of the internal validity of this design with a series of ‘balancing tests’. The aim is to detect to what extent the counties that experience a bigger change in air transport access are comparable to those that experience a smaller change, 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 the access index. 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 transport access and the initial conditions. Counties with bigger

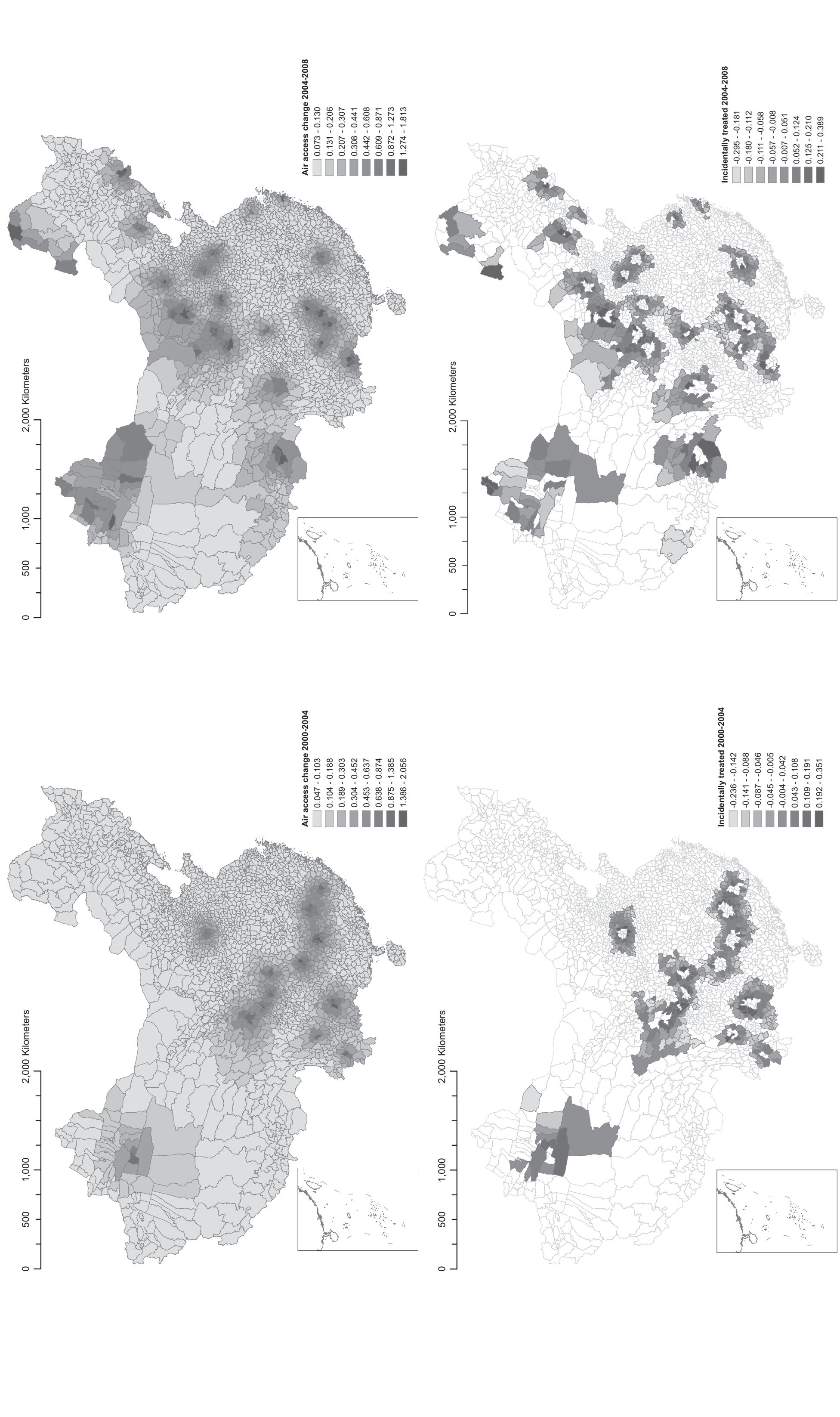

Figure 3. Air transport access changes, 2000–2004 and 2004–2008.

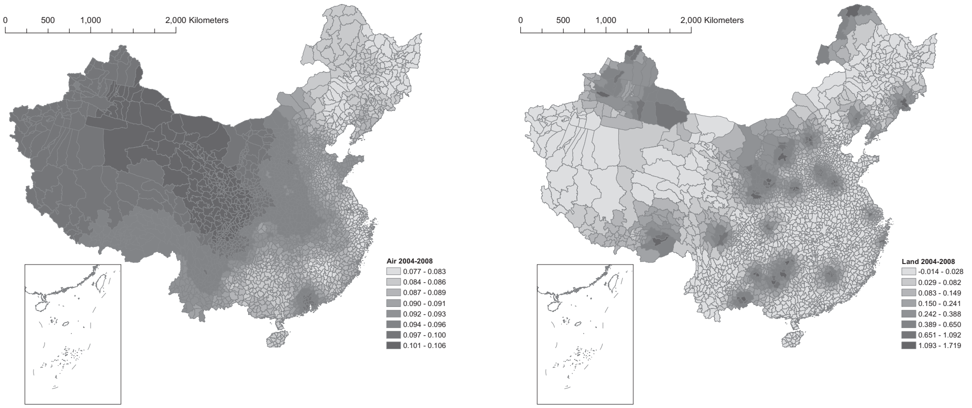

Figure 4. Airside and landside air transport access changes, 2004–2008. Figures show change in ln air transport access index. Left hand panel shows component due to airside changes (changes in flight times between airports). Right hand panel shows variation due to landside changes (changes in distance to nearest local airports).

improvements in 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 transport 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

Table 2 presents the fundamental results from the regressions of changes in industrial firm output on changes in the index of air transport access. The table shows coefficients and standard errors from regression estimates of Equation (3.1), 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 table (and subsequent tables) also reports effect sizes in square brackets, scaled to give an indication of the magnitude of the changes induced by the airport network expansion. These are calculated my multiplying the coefficients by the standard deviation of the 4-year changes in the air access index from the Appendix. 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 of these production functions include controls for firm employment and fixed assets (a second order polynomial in the natural logs of these variables[11]), plus dummies for industry (two-digit). Columns 1 and 2 present estimates on the full sample, first with no geographical controls, secondly

11 The results are insensitive to whether or not we include the employment and capital control variables because these are uncorrelated to the market access changes.

Table 1. Balancing on initial census characteristics and trends

	(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 access	0.0188	0.1467*	0.6855**	−0.5981***	0.0067	−0.5191***	−0.1849*	−0.5046***
	(0.0204)	(0.0851)	(0.2718)	(0.1728)	(0.1267)	(0.1626)	(0.0974)	(0.1761)
Observations	2372	2372	2295	2355	2357	2338	2372	2373
R^2	0.0015	0.0037	0.0105	0.0199	0.0000	0.0162	0.0068	0.0183
Incidentally treated								
Air transport access	0.0127	−0.1340	0.0372	−0.1081	−0.1553	−0.0076	−0.1252	0.1236
	(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
R^2	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 access	0.0027	−0.1608**	−0.0650	0.0623**	−0.5160***	0.6035***	−0.1117*	−0.1520***
	(0.0314)	(0.0795)	(0.0602)	(0.0270)	(0.1831)	(0.1445)	(0.0645)	(0.0578)
Observations	2371	2372	2372	2273	2258	2112	2117	1998
R^2	0.0000	0.0059	0.0022	0.0039	0.0184	0.0103	0.0019	0.0031
Incidentally treated								
Air transport access	−0.0210	−0.0751	−0.0799	0.0949	0.1705	−0.1864	−0.0696	−0.0519
	(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
R^2	0.5287	0.5420	0.5409	0.0882	0.6094	0.2037	0.1451	0.1645

Notes: Pre-treatment variables on changes in log air transport access, 2000–2009. Table reports coefficients and standard errors from regression of county characteristics on 2009–2000 changes in the air transport access index. Air transport access is the 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 (approximately 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 <60% of the distance at beginning. Regressions in incidentally affected group include controls for initial nearest airport fixed effects based on Year 2000 airports (approximately 89). Significance: ***1%, **5%, *10%.

Table 2. Regressions of 4-year changes in industrial firm log gross output on 4-year changes in log air transport 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 access	0.0512	0.0534	0.2582**	0.2591**	0.2612**	0.2838***	0.2109**
	(0.0620)	(0.0377)	(0.1010)	(0.1031)	(0.1007)	(0.0976)	(0.0944)
1 SD effect size	[0.0093]	[0.0097]	[0.0470]	[0.0472]	[0.0475]	[0.0517]	[0.0383]
Observations	43,906	43,906	6,904	6,904	6,904	6,771	6,904
R^2	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	Two-digit	Two digit	Two digit	Two digit	Two digit	Two digit	Two 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

Notes: Table reports coefficients and standard errors from regression of 2005–2009 and 2001–2005 changes in log firm gross output on 2004–2008 and 2000–2004 changes in the air transport access index. Air transport 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 two-digit industry-by-county cells. Standard errors clustered on nearest airport (approximately 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 (approximately 222 in full sample, approximately 107 in restricted sample). Initial access trend control is the air transport access index 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 <60% of the distance at beginning of period. Gross output is nominal. Values deflated using province-year consumer price indices yield almost identical results. Significance: ***1%, **5%, *10%.

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 air transport access and productivity. There is no association between change in air transport access and change in industrial firm output in either specification, though the differences in pre-existing characteristics in Table 1 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 transport 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 the air transport access index in all these regressions is fairly stable at around 0.20–0.28. To understand the magnitude of these effects, we really need to scale in terms of the variation in these air transport access indices, since they have no exact natural economic interpretation. The standardised effects reported in Table 2 imply that counties experiencing a one-standard deviation higher-than-average improvement in air transport access could expect 4–5 percentage points gain in productivity compared to counties on average. As discussed in Section 3.2, these should be interpreted as intention to treat effects, since they are the average causal effect of the implied access change from the provision of new airport transport infrastructure (airports), not the airline services that are actually operated.

The stability of the estimates across different specifications in Columns 3–7 implies that the choice of geographical control variables is largely irrelevant and reinforces the argument that the air transport 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 1, they were evidently targeted towards areas with lower manufacturing employment, higher agricultural employment and slower growth in the high-school educated share).

Table 3 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) which is not available in later years. Only specifications for the incidentally treated group are reported. The coefficients are reassuringly close to those in Table 2, even though this is for a different time span. Again the coefficients are insensitive to the choice of control variable set.

Table 4 triangulates the previous results from the ASIF micro data and presents additional findings from other sectors using administrative records on GDP from the county statistical yearbook data. 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 transport access (in the regression of changes in outcomes on changes in access). Evidently the effects observed in the industrial data analysis are borne out by the results on GDP and 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.

Table 3. Regressions of 6-year changes in value-added 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
Air transport access	0.3036**	0.2561	0.3079*	0.2479
	(0.1453)	(0.1849)	(0.1607)	(0.1536)
1 SD effect size	[0.0553]	[0.0466]	[0.0560]	[0.0451]
Observations	3965	3965	3884	3965
R^2	0.4603	0.4658	0.4625	0.4709
Production input controls	Yes	Yes	Yes	Yes
Industry trends	Two digit	Two digit	Two digit	Two digit
Nearest 2000 airport trends	Yes	Yes	Yes	Yes
Initial access trends	Yes	Yes	Yes	Yes
Additional controls	—	Census and geographic	Pre-2000 population trend dummies	Province dummies

Notes: Table reports coefficients and standard errors from regression of 2007–2001 changes in log firm gross output on 2006–2000 changes in the air transport access index. Air transport 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 two-digit industry-by-county cells. Standard errors clustered on nearest airport (approximately 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 (approximately 57). Initial access trend control is the air transport access index 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 <60% of the distance at beginning of period. Value-added is nominal. Values deflated using province-year-specific consumer price indices yield almost identical results. Significance: ***1%, **5%, *10%.

There are, however, no sizeable or significant impacts on the mining or service sectors. The latter evidence stands in contrast to common assumptions and some previous evidence about the role of air transport in business dealings in finance and other services in developed countries, (Sheard, 2014; Airports Commission, 2015) though is consistent with the effects on tradables in McGraw (2015). This is possibly due to the dominance of manufacturing in China, relative to other sectors, and because the distances involved mean that transporting goods domestically by air is important, though we are unable to shed further light on the mechanisms given the data available.

5.3 Robustness, placebo tests and instrumental variables estimates

The key result so far is that air transport access improvements increased industrial productivity, and we now explore the robustness of this finding to sample and

Table 4. Regressions of 4-year changes in county GDP on 4-year changes in log air transport access, county yearbook data 2002–2006–2010

Geographical subset	(1) GDP Incidentally treated	(2) GDP primary Incidentally treated	(3) GDP secondary Incidentally treated	(4) GDP tertiary Incidentally treated
Air transport access	0.1918** (0.0911)	−0.0032 (0.0790)	0.4164** (0.1649)	0.0007 (0.1291)
Observations	976	919	919	530
R^2	0.3813	0.3959	0.2861	0.3620
Initial airport	Yes	Yes	Yes	Yes
Initial access	Yes	Yes	Yes	Yes

Notes: 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 the air transport access index. Air transport 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 (approximately 125 clusters). All regressions include controls for initial nearest airport × time period fixed, effects based on Year 2000 airports (approximately 125–130 categories). Initial access trend control is the air transport access index in the first year of each period. Incidentally treated geographical subset is the 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 <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. Primary sector is agriculture, forestry and fishery, secondary sector is mining and manufacturing, tertiary sector is services. Significance: ***1%, **5%, *10%.

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 <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 5 starts by presenting results on the sensitivity to this choice of distance buffer. Column 1 presents the preferred estimate from Table 2. 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 2 and the balancing tests in Table 1: 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 or roads (Faber, 2014;

Table 5. 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	(7) Gross output Infrastructure controls
Air transport access	0.2591**	0.2953**	0.2811	0.1565*	0.2628***	0.2524**	0.2704***
	(0.1031)	(0.1372)	(0.1939)	(0.0886)	(0.0869)	(0.1082)	(0.1023)
1 SD effect size	[0.0472]	[0.0537]	[0.0512]	[0.0285]	[0.0478]	[0.0459]	[0.0492]
Observations	6904	5686	4318	7782	6904	5752	6904
R^2	0.4562	0.4638	0.4644	0.4552	0.4616	0.4508	0.4562
Geographical subset or specification	(8) Gross output Drop urban districts	(9) Gross output Minimum 100 k to airports	(10) Gross output Min. 100 km Max 200 km to airports	(11) Gross output Trim top and bottom 5% access change	(12) Gross output Trim top and bottom 5% change in gross output	(13) Gross output First period 2001–2005	(14) Gross output First period 2005–2009
Air transport access	0.2644**	0.3956**	0.3693*	0.3762***	0.1620**	0.1924	0.3494***
	(0.1311)	(0.1860)	(0.2041)	(0.1115)	(0.0782)	(0.1789)	(0.1051)
1 SD effect size	[0.0481]	[0.0720]	[0.0672]	[0.0685]	[0.0295]	[0.0350]	[0.0636]
Observations	5610	3924	3741	6207	6236	3310	3594
R^2	0.4449	0.4629	0.4718	0.4599	0.3489	0.4161	0.5292
Production controls		Yes	Yes	Yes	Yes	Yes	Yes
Industry		Two digit	Two digit	Two digit	Two digit	Two digit	Two digit
Nearest 2000 airport		Yes	Yes	Yes	Yes	Yes	Yes
Lagged access		Yes	Yes	Yes	Yes	Yes	Yes

Notes: Notes as in Table 2. Infrastructure controls in Column 7: distance to highways in 2011, distance to high-speed rail lines open by 2011, change in distance to nearest industrial park or Special Economic zone, between 2000 and 2004, or 2004 and 2008. Significance: ***1%, **5%, *10%.

Qin, 2017). Another concern is that airports may coincide with other industrial policy sites, such as industrial parks and Special Economic Zones (SEZs). However, dropping counties crossed by high-speed rail lines, or controlling for distance to highways and high-speed rail developed over our study period, plus changes in the distance to industrial parks and SEZs makes little difference (Columns 6 and 7). We also checked to see if increases in air access were accompanied by increases in local government expenditure (using the county data, as in Table 4) but found no association. Column 8 in Table 5 drops 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. Evidently, there is some sensitivity to other sample choices. Restricting to counties further away from airports (Columns 9 and 10) or trimming out the largest and smallest access changes (Column 11) yields bigger coefficients; trimming the top and bottom of the distribution of gross output reduces them (Column 12). However, given the standard errors, this variation in different samples is unsurprising. If anything, then the results suggest that our main estimates are conservative and still downward biased by targeting of airports to areas with slower industrial growth.

Columns 13 and 14 compare the effects in the two periods in our data. Clearly, much of the action is from the 2005 to 2009 period which is unsurprising given this period saw the fastest growth in airports although a test of the difference in these coefficients does not reject equality.

Further extending the assessment of the robustness, Table 6 explores alternative measures of air transport access. Column 1 in Table 6 shows the results for the index based on the nearest airport, rather than the nearest 5. The elasticity is smaller than when averaging over five airports although qualitatively the difference is not so large when scaled in terms of standardised effects. The interpretation of this difference is that averaging over more local airports smooths out spatial variation in the access index and reduces its standard deviation: using only a single nearest airport provides a noisy measure of the expected air access in a county, when there are multiple alternative airports available.

The second column of Table 6 allays concerns that our results are influenced by the population weights that enter via the airport destinations in the air transport access index [Equation (3.2)]. The index now excludes these weights so Equation (3.2) 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. An implication of the insensitivity the node weights is that destination airport specific factors like airport size, service frequency and whether or not it has international connections are irrelevant: it is simply the reductions in journey times between counties that drives our results. Modifying the index again, Column 3 changes the assumptions about travel speeds underlying the access index, reducing airspeed by 25% to 600 km/h, increasing land speed to 75 km/h, increasing assumed embarkation/disembarkation times to 1.5 h and dropping all air journeys <300 km. The resulting point estimate is virtually unchanged. Other reasonable modifications to these assumptions produce similar results.

An alternative metric of treatment intensity in Column 4 is simply the reduction in (ln) distance to nearest airport (commonly used, following Gibbons and Machin 2005 for rail stations). This measure focusses only on the landside distance reductions to the nearest airport, ignoring the more general network changes. The sign is in the direction we expect (a reduction in distance increases output) and the elasticity is −0.11, similar in absolute value to that from the air access index based on the nearest airport in Column

Table 6. Alternative air access treatment and placebo

Geographical subset	(1) Gross output Population air access, nearest airport Incidentally treated	(2) Gross output Non population weighted centrality Incidentally treated	(3) Gross output Modified speed assumptions Incidentally treated	(4) Gross output Change in nearest airport ln distance Incidentally treated	(5) Gross output Change in nearest airport ln distance–large, international airports Incidentally treated	(6) Gross output Change in nearest airport ln distance–airports proposed 2010–2020 Incidentally treated
Air transport access	0.0950**	0.2563**	0.2618**	−0.1101**	−0.1096**	−0.1078**
	(0.0423)	(0.1041)	(0.1025)	(0.0444)	(0.0450)	(0.0452)
1 SD effect size	[0.0296]	[0.0492]	[0.0479]	[−0.0311]	[−0.0309]	[−0.0304]
International airport access	—	—	—	—	−0.0356	—
					(0.0904)	
1 SD effect size					[−0.0087]	
Future airport access	—	—	—	—	—	0.0157
						(0.0251)
1 SD effect size						[0.0056]
Observations	6904	6904	6904	6904	6904	6904
R^2	0.4561	0.4562	0.4563	0.4562	0.4562	0.4562
Industry fixed effects	Two digit	Two digit	Two digit	Two digit	Two digit	Two digit
Initial airports	Yes	Yes	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports coefficients and standard errors from regression of changes in outcomes on changes in air transport access. Speeds in Column 4 changed to 600 km/h air speed, 75 km road speed, 1.5 h embark/disembark time, minimum 30-min flight time. For further notes, see Table 2. Significance: ***1%, **5%, *10%.

1. As discussed before, this is a noisier measure of the expected air transport access given a county location with a higher variance.

This alternative distance-reduction measure lends itself to some simple additional tests. In Column 5, we check for whether our results are driven specifically by new international airports (given China's export led growth), rather than the general growth in domestic regional airports. These international airports also correspond approximately to the top quartile in the distribution of airport sizes in terms of numbers of flights. We find no significant difference between the coefficients on the change in distance to large, international airports and airports in general. Column 6 presents a straightforward placebo test to further rule out biases from policy targeting of airports to growing places. In this test, we include an additional variable which is the reduction in (ln) distance to the 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.

Finally, we also explored using the location of historical military airports as an alternative source of exogenous variation in commercial airport location, following a norm in the transport literature (Duranton and Turner, 2012; Baum-Snow et al., 2017). Many airports that were constructed in the 1940s for military purposes were subsequently converted to civil or mixed civil/military uses, usually on the basis of military redundancy rather than any specific local need. We calculate the distance from each county to the nearest military airport in 1943 (using information on military airport locations in 1943 from a hand drawn historical map of China available from the Library of Congress map catalogue, item 2007627806) and use this as an instrument for the changes in air transport accessibility in the 2000s. Unfortunately, the first stage of this two-stage least squares IV regression is fairly weak (an *F*-statistic of 9.4) and the IV coefficient is imprecisely measured with a coefficient of 0.4256 (0.3252). Still, this is of a similar order of magnitude to our main estimates and not statistically different from them. We draw some confidence from the result that an alternative identification strategy, which does not rely on the restriction to the incidentally treated subsample, yields broadly similar results.

5.4 Heterogeneity

So far we have focussed on the average outcomes without considering the marked heterogeneity in the measured effects across a range of industry and county characteristics. Table 7 presents these results. The regressions are estimated by interacting our usual air transport 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

Table 7. Heterogeneity by county–industry characteristics

	(1) Gross output × Extraction and power	(2) Gross output × High K/L	(3) Gross output × Large firms	(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	0.2923**	0.2724**	0.4091***	0.3540***	0.3161***	0.1568
access	(0.1195)	(0.1054)	(0.1173)	(0.1080)	(0.1125)	(0.1088)
1 SD effect size	[0.0532]	[0.0496]	[0.0745]	[0.0644]	[0.0575]	[0.0285]
× Above	−0.1237	−0.0320	−0.2739***	−0.4613***	−0.1637*	0.1817**
median heading characteristic	(0.1605)	(0.0621)	(0.0777)	(0.0744)	(0.0952)	(0.0742)
1 SD effect size	[−0.0225]	[−0.0058]	[−0.0498]	[−0.0840]	[−0.0298]	[0.0331]
Observations	6904	6904	6904	6904	6904	6904
R^2	0.4563	0.4563	0.4579	0.4589	0.4568	0.4569
Production inputs	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Two digit	Two digit	Two digit	Two digit	Two digit	Two digit
Initial airports	Yes	Yes	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table reports coefficients and standard errors from regression of changes in outcomes on changes in the air transport access index. Splits for interactions are based on median values in base period (2001 or 2006) or 2000 for population census variables. For further notes, see Table 2. Significance: ***1%, **5%, *10%.

relatively small firms (average 118 employees) which benefit more than large firms (average 455) from 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 transport access and higher skills, using the share educated to high school level and above as a proxy for skills (Column 5). Note, the share of the population educated to this level is only 17% in 2000, so the high school share is a better proxy for high skill than it would be in Europe or the USA. This finding is not very supportive of a story of these effects being driven by information sharing and face-to-face interaction amongst high skill groups specifically—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 Airside versus landside access

In the final part of the empirical analysis, we turn to the decomposition of air transport access into airside and landside components, as set out in Equation (3.3). The results of this decomposition are in Table 8, where we show the results for gross industrial output and value-added (ASIF data), and secondary GDP (from the county statistical year book data). The first group of rows shows the coefficients and standard errors related to landside distance reductions. The second group of rows relate to airside access. Note,

Table 8. Decomposition of airside and landside population access changes

Geographical subset	(1) Gross output Incidentally treated	(2) Value-added Incidentally treated	(3) Gross output Incidentally treated	(5) Secondary GDP Incidentally treated
Landside airport	0.2268**	0.2691*	0.3183*	0.4231**
access	(0.1071)	(0.1471)	(0.1787)	(0.1676)
Effect size	[0.0313]	[0.0371]	[0.0439]	[0.0584]
Airside network access	−10.8398	−9.6502	4.1628	3.7998
	(7.3896)	(12.3606)	(7.9177)	(10.2526)
Effect size	[−0.1300]	[−0.1158]	[0.0500]	[0.0456]
Observations	6,904	3,965	847	919
R^2	0.4566	0.4317	0.6458	0.2862
Industry fixed effects	Two digit	Two digit	—	—
Initial airports	Yes	Yes	Yes	Yes
Lagged access	Yes	Yes	Yes	Yes

Notes: Table reports coefficients and standard errors from regression of changes in outcomes on changes in the air transport access index. Air transport 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 and 5). Standard errors clustered on nearest airport. All regressions include controls for initial nearest airport × time period fixed, effects based on Year 2000 airports. Initial access trend control is the air transport access index in the first year of each period. Columns 1 and 2 include two-digit industry fixed effects. Incidentally treated geographical subset is the 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 <60% of the distance at beginning of period. Significance: ***1%, **5%, *10%.

the standard deviation of the airside access changes over space is <10% of that attributable to landside changes—see Table 4 and Figure 4. This is true over China as a whole, as well as in the restricted incidentally treated subsample: the variation in accessibility generated by new airport construction is largely a feature of reducing the distances by land to the nearest airport. The effect of a one standard deviation change is shown in square brackets, to make the effect sizes of these airside and landside changes comparable.

The landside results are in line with the results presented on overall air transport access so far: positive and significant for industrial output, value added, secondary GDP. Results on airside access are more varied. When we estimate on the ASIF industry–county panel and allow for industry-specific fixed effects and trends (Columns 1 and 2) we find large, negative and insignificant effects from airside access. These within-industry effects imply that the availability of potential destinations, once a local airport is reached, has adverse impacts on output in existing industries—perhaps due to penetration of non-local suppliers into the local markets. However, when we remove the industry fixed effects and estimate on a county-level panel (Column 3) or when we look at secondary GDP at county level (from the administrative yearbook data), the effects become positive, although still insignificant. Evidently, network effects of airside access potentially improve local industrial output once we include changes in industrial composition, although the effects are imprecisely estimated due to the limited local variation in airside access.

6. Conclusion

We provide new evidence that the rapid expansion of air transport infrastructure in China over the 2000s led to substantial growth in industrial output, productivity and GDP, using firm-level and county-level datasets. The estimates are based on a design that focuses on 'incidentally' affected counties, whose location midway between existing and new airports implies they were not explicitly targeted for development nor directly affected by airport operations. Our measure of treatment is an index of changes in air transport access between counties, given the location of new and existing airports, which we decompose into air and landside components.

We reach three main conclusions. First, improved access due to landside distance reductions implied by building new airports leads to higher industrial productivity. Our 'intention to treat' estimate of the elasticity of productivity to changes in the expected air access index in a county arising from new airport construction is 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. Secondly, most of the variation in air transport access generated by construction of new airports comes from reduction in the land side travel times, so the main gains to manufacturing come from the landside cost reductions. This highlights 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 an effect from airside availability of destination airports on industrial output although this is imprecisely measured. Thirdly, though we find a positive effect on manufacturing and the wider industrial sector, we find no clear effects on GDP in the service sector, which runs counter to common assumptions and some previous evidence about the role of air transport in business dealings in finance and other services in developed countries. The finding is, however, consistent with

McGraw (2015) who finds bigger effects on tradables. Broadly speaking, the analysis suggests that airports favoured smaller manufacturing firms, with higher shares of private ownership, in low skill, urban counties. We cannot, of course, contribute anything in this article regarding the environmental costs and benefits of air transport versus roads and rail.

The airport construction policy in China appears to have been successful in boosting local growth in the manufacturing sector. The standard deviation in the change in our index of air transport access (based on 4 year changes) is 0.18, implying that firms in counties experiencing a one standard deviation higher than average improvement could expect around a 4.5% higher than average increase in productivity. Extrapolating our estimates to the national level, the 35% increase in access between counties 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. These facts suggest that our findings are more likely attributable to micro-level productivity improvements. To the extent that these results can be generalized to other fast-urbanising, developing country settings, the implication is that air transport infrastructure has an important role to play in developing economies like China where distances are vast and manufacturing plays a dominant role.

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Appendix A: construction of the air market access/centrality indicator

Construction of the air transport access index in Equation (3.2) 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 Geographical Information System (GIS), and converted into imputed flight times using an assumed average flight speed: 800 km/h in the main estimates, 600 km/h in the presented robustness checks. Airport-to-airport links below a minimum threshold are dropped: 200 km in the main estimates, 300 km in robustness checks. Fixed time costs are added to all links to allow for embarkation and disembarkation: 1 h in main estimates, 1.5 h in robustness checks. 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 (3.2) and the Year 2000 populations of the counties in which airports are located. This is effectively a population potential index (Harris, 1954), using imputed flight times rather than distances in the denominator.

To obtain approximate landside 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 65 km/h. For each year, these point airport times are then used to discount the airport-specific access measures calculated as described above. These discounted air 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 transport access indicators (dividing by the number of points in a county to avoid double counting). The average 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 average index in a county given its position relative to the five nearest airports, where each airport's own market access indicator is discounted by landside distance. Note, to obtain the components needed to calculate the land side and airside-specific indices of Equation (3.3) requires four component indices: (i) the first term is the full set of airport-specific accessibility indices in year t, discounted back to counties using the set of local airports available in Year t; (ii) the second term is the full set of airport-specific accessibility indices in Year t, discounted back to counties using the set of local airports available in Year $t - s$; (iii) the third term is the same as the second; and (iv) the fourth term is the full set of airport-specific accessibility indices in Year $t - s$, discounted back to counties using the set of local airports available in Year $t - s$.

Appendix B: descriptive statistics

Table A1 shows summary statistics for the key variables in our data set. The top panel summarises the estimation data for the industrial firms analysis (a two-digit industry-by-county-by year panel), the bottom panel summarises the county statistical yearbooks panel used for GDP. 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 <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 two-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 eight rows present a range of figures related to the change in distance to local airports and the change in air transport access. The baseline absolute level of the air transport 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 transport 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 with 15% when we look at changes in the industrial firms panel (spanning 2001–2009), 30% compared with 18% in the county statistical panel (spanning 2002–2010). Note, there is little difference in the means when we compare 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 landside and airside components. Note, in line with Figure 4, there is much less variation in airside access between counties than there is landside access, and landside 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.

Table A1. Summary statistics for county and industrial data

Industrial data, 2001–2005, 2005–2009	Full $N = 43{,}906$				Restricted $N = 6904$			
Two-digit industry × county × 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 transport access (5 airp.)	0.151	0.182	0.047	1.9	0.31	0.138	0.052	0.81
Change in ln air transport access (1 airp.)	0.158	0.312	0.046	3.135	0.312	0.291	0.053	1.177
Change in ln landside air access	0.075	0.179	−0.014	1.839	0.229	0.136	−0.006	0.711
Change in ln airside air access	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 × 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 transport access (5 airp.)	0.178	0.184	0.05	1.917	0.303	0.135	0.063	0.816
Change in ln air transport access (1 airp.)	0.186	0.324	0.054	3.145	0.302	0.28	0.054	1.173
Change in ln landside air access	0.095	0.183	−0.015	1.848	0.218	0.133	-0.013	0.711
Change in ln airside air access	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 <60% of the distance at beginning of period.