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Small airports: Runways to regional economic growth?

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ABSTRACT

Regions typically take great pride in having an airport within their boundaries. Policymakers go through great lengths in maintaining and sustaining airports, small as some of them may be. This support is often justified by pointing out the potential positive economic spin-off of the airport. This study adds to the body of literature on the role of airports in economic growth by assessing the link between air accessibility – with a focus on smaller airports - and regional economic development across European regions. We take into account spatial and airport heterogeneity as well as overlapping catchment areas. The data set consists of a strongly balanced panel of 274 European NUTS-2 regions spanning the years 2000–2018. For most regions, the contribution of smaller airports in providing accessibility is found to be limited. Nevertheless, in 2018, air accessibility for 19% of the European population covered is provided mainly by medium-sized and small airports, and for 3% mainly by small airports. The long-run elasticity between air accessibility and GDP per capita is estimated at 0.106 and is stronger for large airports (0.179) than for medium-sized (0.033) and small airports (0.022). Causality mainly runs from economic growth to air accessibility, especially considering smaller airports. However, considerable spatial heterogeneity exists in the nature of this causal relationship, with dense regions with lagging per capita GDP levels especially benefiting from air accessibility.

1. Introduction

Liberalizations in the European air transport market during the nineteen-nineties have paved the way for the rise of low-cost carriers (LCCs). This has triggered the creation, expansion and commercialization of smaller airfields, as LCCs prefer uncongested airports to minimize operating and handling costs (Barbot, 2006; Barrett, 2004; Thelle and La Cour Sonne, 2018; Zhang et al., 2008). These airports, which are often referred to as 'regional' airports, are often owned or supported by local governments that try to boost international connectivity and, consequently, economic growth. The competition between airports regarding attracting airlines is characterized by low bargaining power on the airport's side, as footloose LCCs as well as footloose consumers are both able to easily switch between airports to minimize costs (Guillen and Ashish, 2004; Thelle and La Cour Sonne, 2018). While some airports have been successful in attracting traffic, most remain rather small and exhibit unstable networks (Redondi et al., 2012). In 2018, the vast majority of European airports (80%) handled fewer than 5 million passengers, and more than half (57%) handled fewer than 1 million passengers (Eurostat, 2020). Low and often fluctuating traffic volumes have resulted in around half of these airports operating at a loss while relying on public treasuries for their upkeep (ECA, 2014; Francis et al., 2004).

This situation sparks the question of how important accessibility provided by smaller airports is for regional economies. The question has increased salience now that the public support of smaller airports will be further regulated in the European Union (EU) as of 2024 (European Commission, 2014). Given the already shaky position of many of these airports, more stringent regulations concerning state aid will potentially lead to closures and possibly decreased accessibility and economic development (ACI Europe, 2020; Breidenbach, 2020). In response, this paper sets out to evaluate the contribution of smaller airports to air accessibility in Europe as well as the strength of the link and direction of causality between air accessibility and economic development in Europe, focusing in particular on smaller airports.

Evidence regarding the link between air transport and economic growth is inconclusive (Zhang and Graham, 2020). While most studies suggest the existence of positive economic spillovers, the analysis of causality is hampered by potential feedback effects (Green, 2007; Zhang and Graham, 2020). Several reasons may be at the source of the inconsistent evidence. First, the way airport activity and potential spillovers are measured matters. While they are often measured at the

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regional level (e.g. Blonigen and Cristea, 2015; Fu et al., 2021; Van de Vijver et al., 2016), economic effects of air traffic may occur outside the administrative unit in which air traffic is generated, as catchment areas are not confined to administrative units. Alternatively, spillovers can be measured at the airport level using distance bands (e.g. Breidenbach, 2020). However, effects from a single airport are then difficult to discern since airport catchment areas may overlap (Lieshout, 2012). Inadequately measuring air accessibility may subsequently lead to spurious conclusions regarding economic impacts and causality. Second, effects may differ across types of airports. Especially in the European context, the economic impact of smaller airports is suggested to be limited (e.g. Breidenbach, 2020; ECA, 2014; Tveter, 2017). Finally, the direction of causality between aviation and economic growth may be spatially heterogeneous (Mukkala and Tervo, 2013). Especially in this regard, it is important to correctly assess air accessibility since positive spillovers may exist outside the administrative region of an airport. However, a systematic analysis of where a given direction of causality is more likely is lacking from the literature (Zhang and Graham, 2020).

This paper adds to the literature in several ways. A longitudinal design spanning the years 2000–2018 is used. This allows testing for causality in either direction based on time-series analyses. Airport activity is measured through a gravity-based potential accessibility measure for all European NUTS-2 regions.[1] In this way, it is possible to capture spillovers outside the administrative region of an airport and to account for overlapping catchment areas. Models are estimated to identify which regional characteristics are associated with high air accessibility and high dependence on smaller airports. To account for spatial heterogeneity in the relationship between aviation and economic growth, various estimators for heterogeneous panels are employed (Pedroni, 2001; Pesaran and Smith, 1995) and causal relationships are inferred at the regional level (following Canning and Pedroni, 2008). All models are estimated for airports in general as well as seperately for large, medium-sized and small airports. Finally, this paper also estimates models explaining the direction of causality using various regional characteristics.

The paper is organized as follows. The next section will elaborate on the theoretical argument of how air traffic and economic growth are connected and reviews the associated empirical literature. Section 3 describes the data and methods used of which the results are presented in section 4. Section 5 is dedicated to the discussion and following conclusions, respectively.

2. Literature review

2.1. Air accessibility and economic growth

Four main channels of economic impacts from aviation can be identified (Zhang and Graham, 2020). The first three channels follow the logic of input-output studies. Airports have direct, indirect and induced effects on the economy following the operation of the airport itself. Direct impacts arise from activities at the airport directly related to the operation of the aviation industry (airport operation, traffic control, ground handling, etc.). Indirect impacts are generated by upstream activities that facilitate activities at the airport (fuel suppliers, travel agents, etc.). Completing the set of 'supply-chain effects', induced impacts comprise all impacts generated by the spending of households employed directly or indirectly by the aviation industry. The associated multiplier may be substantial. As an example, Hakfoort et al. (2001) suggest a total multiplier of around 2.0 of direct employment at Schiphol, the largest airport in the Netherlands. Since the fixed costs and associated employment are relatively large for airports, the local multiplier may be even larger for airports in smaller regions.

In addition to the economic effects connected to the operation of an airport, there are spillover effects associated with the connectivity offered by an airport. Connectivity may drive productivity growth and attract new economic activities through facilitating face-to-face contacts. Advanced industrialized economies increasingly compete in terms of high value-added services embodying complex knowledge and information. Valuable information about engaging in and coordinating economic activities in these sectors is of a non-standardized, tacit nature, which increasingly requires personal contacts with customers, suppliers and employees (McCann and Shefer, 2004; Storper and Venables, 2004). In the current era of globalization in which multinational companies are one of the main drivers of economic growth, markets may extend well beyond country borders. This means that, next to agglomeration, global connectivity increasingly is crucial to the way regions compete (McCann and Acs, 2011). Air accessibility may facilitate face-to-face interactions and thus increase productivity, especially in the service sector, which increasingly competes on knowledge-intensive activities. In addition, the presence of an airport may have a more intangible effect, as it signals a vibrant regional business environment. As such, it may play a role in the regional economic image.

2.2. Empirical findings

In line with the conceptual argument of the previous section, the correlation between air transport and economic growth is empirically evident. In contrast, the direction of causality of the relationship is less clear since feedback effects occur as economic success generates demand for aviation and facilitates the construction of airport infrastructure. After accounting for such feedback effects through instrumental variables estimation or quasi-natural experiments, studies are generally still able to establish evidence that air transport positively affects economic growth (Blonigen and Cristea, 2015; Bilotkach, 2015; Brueckner, 2003; Doerr et al., 2020; Gibbons and Wu, 2020; Percoco, 2010; Sellner and Nagl, 2010; Sheard, 2014, 2019, 2021). Studies explicitly considering the direction of causality using time-series analyses also confirm the presence of positive spillovers (Brida et al., 2016; Button et al., 1999; Chi and Baek, 2013), but also show that the relationship between air transport and the economy can be bidirectional (Hu et al., 2015; Marazzo et al., 2010). Since the causal linkages appear difficult to disentangle, there is no consensus regarding the nature of the relationship between aviation and the economy (Green, 2007; Zhang and Graham, 2020).

Three sources may be identified for the inconclusive evidence regarding the causal linkages between aviation and the economy. First, air accessibility is usually measured by air traffic measures at the airport or regional level (e.g. Antunes et al., 2020; Dziedzic et al., 2020; Florida et al., 2015; Iyer and Thomas, 2021; Van de Vijver et al., 2016). Yet, it is plausible that economic effects of air traffic occur outside the administrative unit in which air traffic is generated since airport catchment areas are not confined to these units (Lieshout, 2012). Also, airport catchment areas are likely to overlap, making it difficult to tease out the impact of a single airport. Accessibility measures that capture overlapping catchment areas are seldom used in air transport studies (Van Wee, 2016). As an exception, based on an index on the municipal level derived from travel times to other municipalities, explorative analyses of Redondi et al. (2013) show for Western Europe that the omission of small airports only leads to significant increases in travel times in Scandinavian countries and peripheral regions in France and Spain. This suggests that most regions are well-served by larger airports outside their administrative unit that can take over the accessibility offered by the smaller local airport. If the overlap of catchment areas is not taken into account, the role of smaller local airports in providing accessibility and potential economic growth is likely overestimated.

Second, impacts may differ among airport types. Spillover effects

[1] The NUTS (Nomenclature of Territorial Units for Statistics) classification is a hierarchical system that divides the economic territory of the EU and the United Kingdom into 104 regions at the NUTS-1 level, 283 regions at the NUTS-2 level and 1,345 regions at the NUTS-3 level.

connected to accessibility and traffic generated by an airport are likely more pronounced for larger airports, even though the impact may dissipate across the entire catchment area. Evidence on positive spillovers from smaller airports is more ambiguous. Significant impacts of smaller airports have been identified in Australia and New Zealand (Baker et al., 2015; Fu et al., 2021) but could not be confirmed for Germany and Norway (Breidenbach, 2020; Tveter, 2017).

Opposing results in different geographical contexts means that spatial heterogeneity may constitute a final source of inconclusive evidence (Chi, 2012; Hakim and Merkert, 2016; Mukkala and Tervo, 2013; Tolcha et al., 2020; Van de Vijver et al., 2014, 2016). Comparing the available empirical results suggests that less developed and peripheral regions benefit more from air traffic (Zhang and Graham, 2020). This is consistent with the idea that large fixed costs for an airport guarantee a relatively large impact of airports in regional economies. This means that, although larger airports may be expected to generate larger impacts, small airports may especially be important in smaller regions. Given the opposing direction of the mechanisms at play, the net outcome of airport and spatial heterogeneity regarding the link between air traffic and economic growth is an empirical matter.

3. Data and methods

The empirical analysis has two consecutive steps. First, the contribution of smaller airports to air accessibility in Europe is determined. The second part of the analysis aims to establish and explain potentially spatially heterogeneous long-run and causal relationships between air accessibility from airports of different sizes and regional economic output.

3.1. Data

The data set used is a strongly balanced panel covering air accessibility and economic development across 274 European NUTS-2 regions for the period 2000–2018. For the calculations of regional air accessibility (see Section 3.2), data on the number of passengers handled at the airport level is gathered through Eurostat. We include all airports with commercial passenger services located in countries in the European Economic Area (EEA) (including provisional member Croatia but excluding Iceland), the United Kingdom and Switzerland. Missing information has been complemented using annual reports issued by airports or national air traffic agencies. Regional levels of gross domestic product (GDP) per capita, which are also freely available from Eurostat, are used to measure economic development. As GDP comprises all economic transactions, it is an appropriate measure to capture both the economic effects of the airport itself and the spillovers generated through the connectivity provided by the airport. To facilitate spatial comparability, per capita GDP levels were corrected for price level differences. Our choice to use GDP per capita rather than absolute levels corresponds to our focus on assessing the link between air accessibility and economic performance rather than sheer market size. Nevertheless, we tested both possible measures and found a strong correspondence between the results (see section 4.2.2). This means that both measures are closely aligned regarding their relationship with air accessibility.

To capture potentially heterogeneous effects across different types of airports, this paper adopts a size-based classification as set by the European Commission (2005). Airports handling more than 5 million passengers per year are classified as ‘large airports’, between 1 and 5 million as ‘medium-sized’ and fewer than 1 million as ‘small’. For the longitudinal analyses, this classification is set at the first year of the estimation period (2000) for the classification to be consistent during the whole panel duration.

Table 1 presents summary statistics on the airport classes. Between 2000 and 2018, air traffic numbers in terms of passengers handled have grown drastically. The median airport size in each class has at least doubled. However, despite this growth, there is a large consistency regarding relative airport size within all classes. Ranking all airports based on size and comparing rank numbers between 2000 and 2018 using paired *t*-tests yielded no significant differences.

It should be noted that the terminology of ‘medium-sized’ and ‘small’ airports cannot be directly interchanged with ‘regional’ airports, often done in the debate on providing state aid, as such a typology also involves characteristics of the geographical context (Dobruszkes et al., 2017). Although smaller airports are on average located in more peripheral locations, further away from urban concentrations, some small airports (e.g. London City) do not typically correspond to the term ‘regional’ in public and policy discourses while some other larger airports do (e.g. Charleroi).

3.2. Air accessibility

The first step of the analysis is to calculate regional levels of air accessibility. Accessibility is in essence the potential to interact with opportunities at a distance. As such, it is a combination of the magnitude of opportunities at destinations and the impedance of getting to these destinations (Van Wee, 2016). More formally, accessibility can be captured in the following general specification:

$$ACC_i = \sum_j O_j f(c_{ij}) \tag{1}$$

where ACC_i represents air accessibility in region $i = 1, \ldots, N$, O_j represents the magnitude of opportunities (see Section 3.2.1) provided at airport $j = 1, \ldots, J$, and $f(c_{ij})$ represents an impedance function of the costs c_{ij} of reaching airport j from region i (further specified in Section 3.2.2). In the context of this paper, this means that air accessibility in a given location is the sum of opportunities provided at airports serving the region, which is weighted by the costs of reaching those airports.

The exact location from which regional air accessibility is calculated needs careful consideration. Straightforward methods include using a region’s main population centre or a region’s mean centre, which can be population-weighted. However, one could easily think of spatial configurations in which such methods would lead to misleading results.[2] To represent an average for all inhabitants in a certain region, air accessibility is calculated for each urban cluster[3] in a region from which then a population-weighted average is taken. This corresponds to the following specification:

$$ACC_i = \frac{\sum_{u \in U_i} \sum_j w_u O_j f(c_{uj})}{\sum_{u \in U_i} w_u} \tag{2}$$

where w_u represents the population-based weight attached to urban centre u that is part of the set of urban clusters U_i located in region i.

3.2.1. Airport connectivity

The number of opportunities (O_j in Eqs. 1 and 2) is defined as the connectivity offered at an airport. Airport connectivity is the degree to which a node is embedded in the entire network, both in terms of the number of connections and the quality of the connection. This includes connectivity provided at destination airports, the economic importance

[2] Think, for example, of a rectangular administrative unit with two equally sized cities in the bottom corners of which one of them is located near an airport. This means that people in the airport city experience higher air accessibility than those in the non-airport city. Using one of the two cities would either result in an over- or underestimation of the average level of air accessibility for all people in the region, depending on whether the airport city is chosen or not. Using the mean centre or population-weighted mean centre would both result in an underestimation.

[3] Urban clusters ($N = 8{,}487$) represent groups of adjacent raster cells of 1 km^2 with a population density of at least 300 inhabitants/km^2 and a total population of at least 5,000 (Eurostat, 2016).

Table 1
Airport descriptive statistics.

Airport class based on passengers handled in 2000	Number of airports	Median airport size, 2000	Median airport size, 2018	Mean airport size rank number difference[a], 2000 vs. 2018	Mean road distance to nearest city[b] (km)
Large airports	48 (11%)	10,238,000 (Berlin-Tegel)	24,130,121 (Athens)	−2.67 (11.9)	15.3
Medium-sized airports	78 (18%)	1,998,011 (Strasbourg)	4,106,711 (Turin-Caselle)	−4.41 (6.42)	20.1
Small airports	305 (71%)	114,144 (Chambéry-Savoie)	237,225 (Łódź-Lublinek)	1.55 (4.47)	31.3

[a] Standard errors in parentheses.
[b] Defined by Eurostat as a local administrative unit (LAU) where the majority of the population lives in an urban centre of at least 50,000 inhabitants.

of destination cities, service frequencies, route directness, flight durations, and so on (Burghouwt and Redondi, 2013). A comprehensive analysis would include as many of these dimensions as possible, carefully weighing them against each other in a final connectivity index. Apart from the difficulty of obtaining reliable comparable longitudinal data on these aspects for all airports, it is uncertain how such a weighting of connectivity dimensions should be carried out.

Given these limitations, we adopt the number of passengers handled as an approximation of airport connectivity, by-passing the need for expensive data sources and constructing complex weighing schemes, but recognizing the restrictions it will place on our interpretation of the results. Although air traffic is not the same as connectivity, as it does not include any explicit network characteristics, they are closely linked. Given relatively fixed aircraft sizes, it can be assumed that the number of passengers translates into the number of flights and the range of destinations available. This association is confirmed when publicly available NetScan (Boonekamp and Burghouwt, 2016) and IATA airport connectivity scores (InterVISTAS, 2015) for 2016 and 2013 are benchmarked against the number of passengers, yielding correlation coefficients of 0.93 and 0.88, respectively. It should be noted that these correlations are typically slightly lower for small airports and considerably lower for medium-sized airports. This latter class of airports consists of both relatively large airports operating point-to-point networks and relatively small airports serving regional centres and operating networks of relatively high quality. Since this paper focuses on heterogeneity between airport classes and not within these classes, such a higher variability in actual connectivity within a class should not jeopardize the goal of the study. Another justification for basing the accessibility measure on passenger numbers is that productivity spillovers can mainly be expected to come from actual air traffic rather than potential connectivity, which may be unrealized (Sheard, 2014).

3.2.2. Air accessibility impedance function

The cost function ($f(c_{uj})$ in Eq. 2) is based on the road distance[4] from an origin u to an airport j. Road distances are calculated using the Global Roads open access data set (gROADS) (Center for International Earth Science Information Network CIESIN et al., 2013). Following spatial interaction theory, we adopt a gravity-based function. Although the actual form of this function is uncertain and likely to be heterogeneous across airports due to spatial competition and border effects (Fröhlich and Niemeier, 2011; Paliska et al., 2016; Zijlstra, 2020), the exponential and power-based functions dominate the literature employing gravity-based specifications (De Vries et al., 2009; Melo et al., 2012). Power functions generally overestimate short-distance interactions and are better suited to model long-distance behaviour such as migration flows (Fotheringham and O'Kelly, 1989). Exponential decay functions are typically used to model shorter distance interactions, including travel behaviour (Handy and Niemeier, 1997). Therefore, the impedance function in Eq. (1) is defined as:

$$f(c_{uj}) = \exp(-\gamma c_{uj}) \tag{3}$$

where c_{uj} is the road distance between origin urban cluster u and airport j, and γ is a cost sensitivity parameter.

Setting the cost sensitivity parameter γ relates to the size of an airport's catchment area. These areas are likely to be influenced by the individual airport's level of service and that of its competitors as well as regional socio-economic characteristics (Fröhlich and Niemeier, 2011; Lieshout, 2012; Zijlstra, 2020). Accordingly, γ is likely to be unique for each origin and destination pair. However, determining unique sensitivity parameters is beyond the scope of this paper and not feasible as it would require extensive data on airport service quality and on travel behaviour between all airports and regions, which are not available. Therefore, this paper uses a pre-set cost parameter. Specifically, it is assumed that $\gamma = 0.025$.

This value of γ is reasonable considering earlier studies of airport catchment areas. Most studies assume distance bands between 100 and 200 km (Maertens, 2012; Marcucci and Gatta, 2011). A cost parameter of about 0.025 corresponds to a weight of 0.01 at 200 km. Zijlstra (2020) finds a median travel distance to a selection of European departure airports of 49 km. Our specification suggests a lower weight at this distance (0.29) but is however plausible given that economic impact is likely the result of inbound business and tourism passengers who are more sensitive to airport egress rather than access times. Although the parameter is in line with previous studies, it inevitably exhibits a certain level of uncertainty in the absence of data to estimate the actual distance decay. Therefore, other cost parameters ranging from 0.015 to 0.1 are also tested to assess the sensitivity of the results to different assumptions on spatial interaction.

3.3. Air accessibility and economic development: Cointegration and Granger causality

When assessing the relationship between air accessibility and economic growth, we first examine the time-series properties of the variables involved before estimating the relationships and evaluating directions of causality. Fig. 1 displays a plot of the panel averages air accessibility for all airport classes as well as for per capita GDP, which is used to capture economic effects. All variables are in natural logarithms and per capita.[5] As the main goal of this graph is to observe how the series evolve rather than evaluating absolute levels, air accessibility values for different airport types are standardized for clarity of display.

The overall upward trends suggest that the series are not stationary. Rather they seem to inhibit stochastic trends, that is, they are integrated of order one, denoted as I(1). Estimating a relationship between two upwardly trending variables can easily produce a statistically significant

[4] The justification for using road distances is that the share of kilometres travelled by passenger car and bus is by far the largest of all ground transport modes (92.5% in 2012) (Eurostat, 2014).

[5] Per capita values are used to capture scale effects (i.e. a given level of air accessibility is expected to be more significant in regions with a small population than in a larger region).

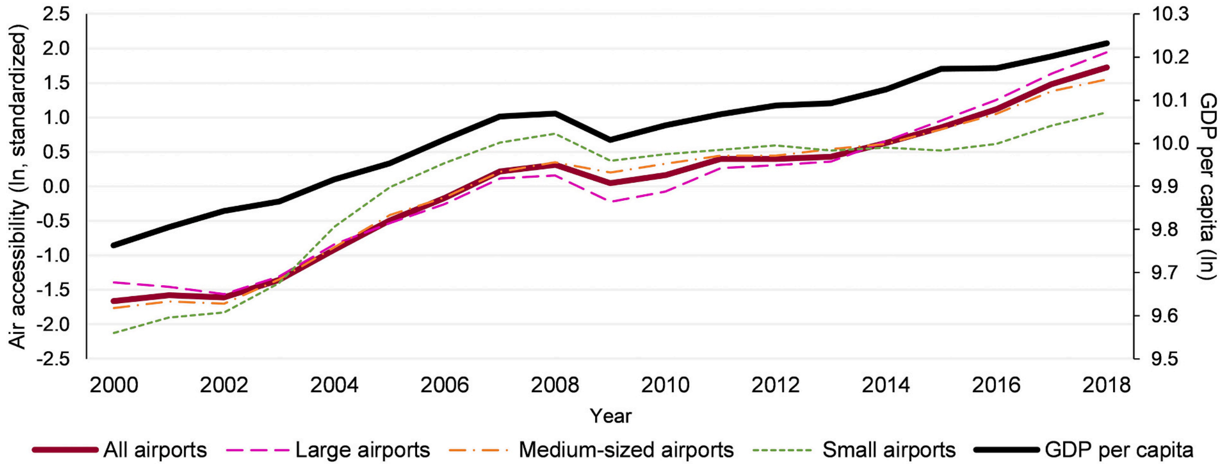

Fig. 1. Panel mean time series plots.

relationship, while in reality they are not connected. However, the air accessibility and GDP series seem to follow similar paths without deviating much over time, leading to the suggestion that the linear combination of one of these series with the GDP series may cancel out the stochastic trends, leaving the error term stationary. In such a situation of cointegration, there is a non-spurious estimable long-run equilibrium relationship between the series, allowing for the assessment of causality directions (Engle and Granger, 1987). Also note that the variables seem to be subjective to shocks that may be common to all regions, most notably the financial crisis of 2008. This leads to the suspicion of a strong cross-sectional dependence, meaning that the variables are correlated among panel members. This has to be taken into account to obtain unbiased estimates. The following sections examine more formally the existence of cross-sectional dependence, the order of integration of the variables involved and the existence of cointegration, after which the procedure of evaluating long-run relationships and directions of causality are set out.

3.3.1. Cross-sectional dependence

Table 2 presents the results of the cross-sectional dependence (CD) test by Pesaran (2004).[6] To test the nature of this dependence, the exponent α-test of Bailey et al. (2016) has been applied. The latter statistic can take values on the interval (0,1], where $\alpha \leq 0.5$ suggests weak cross-sectional dependence and $\alpha = 1$ strong cross-sectional dependence.

The presence of global common factors is confirmed for all variables following the significant CD-test statistics while the values of α are not significantly different from 1.

Table 2
Tests for cross-sectional dependence.

	CD-test	Exponent-α
$\ln GDP$	705.2***	1.003 (0.080)
$\ln ACC_{total}$	658.2***	1.002 (0.024)
$\ln ACC_{large}$	627.5***	0.988 (0.039)
$\ln ACC_{medium}$	604.1***	0.997 (0.019)
$\ln ACC_{small}$	320.9***	0.991 (0.016)

All variables are per capita. The CD-test operates under the null hypothesis of weak cross-sectional dependence. Standard errors in parentheses. ***p < 0.01.

3.3.2. Order of integration

To assess the order of integration of the variables involved, Harris–Tzavalis (HT) and Im–Pesaran–Shin (IPS) panel unit root tests are performed and presented in Table 3 (Im et al., 2003; Harris and Tzavalis, 1999). Both tests are suitable for panels with large N and fixed T. The latter also allows for individual autoregressive parameters. Demeaned versions of the tests account for strong cross-sectional dependence (Levin et al., 2002). All tests include regional fixed effects and time trends in the level versions to control for the general upward trend in all series.

In no case, the null hypothesis that every region has a unit root for the series in levels could be rejected. When testing for a unit root in first differences, the test statistic is significant in each case. This indicates that all variables are stationary in first differences and, therefore, I(1).

3.3.3. Cointegration

Turning to the question of cointegration between air accessibility and GDP per capita, the cointegrating regression is:

$$\ln GDP_{it} = a_i + \beta_i \ln ACC_{it} + e_{it} \tag{4}$$

where $\ln GDP_{it}$ represents the natural logarithm of per capita GDP for regions $i = 1, \ldots, N$ in year $t = 1, \ldots, T$. Likewise, $\ln ACC_{it}$ represents the natural logartithm of per capita air accessibility as defined in Eq. (2) for the same regions and years. Region-specific intercepts are represented by a_i, and e_{it} is the residual term.

Cointegration tests estimate Eq. (4) and test for stationarity of the residuals (see Table 4). The test by Kao (1999) assumes an equal cointegrating vector across all panel members, which restricts $\beta_i = \beta$ in Eq.

Table 3
Panel unit root statistics.

	HT (ρ)	HT demeaned (ρ)	IPS ($\bar{t}$)	IPS demeaned ($\bar{t}$)
$\ln GDP$	0.679	0.709	−2.211	−2.043
$\ln ACC_{total}$	0.764	0.759	−1.840	−1.942
$\ln ACC_{large}$	0.658	0.642	−1.963	−1.961
$\ln ACC_{medium}$	0.825	0.825	−1.743	−1.877
$\ln ACC_{small}$	0.775	0.745	−1.825	−1.872
$\Delta\ln GDP$	0.087***	0.070***	−3.709***	−3.726***
$\Delta\ln ACC_{total}$	0.248***	0.181***	−3.081***	−3.196***
$\Delta\ln ACC_{large}$	0.241***	0.185***	−3.293***	−3.497***
$\Delta\ln ACC_{medium}$	0.288***	0.251***	−3.037***	−3.186***
$\Delta\ln ACC_{small}$	0.153***	0.087***	−3.354***	−3.481***

All variables are per capita. All tests operate under the null hypothesis of a unit root in all panels. HT tests have the alternative hypothesis of stationarity in all panels. IPS tests have the alternative hypothesis of stationarity in some panels. All tests contain time trends (region-specific in the IPS tests). ***p < 0.01.

[6] The Pesaran (2004) CD test is defined as: $CD = \sqrt{2T/N(N-1)}\sum_{i=1}^{N-1}\sum_{r=i+1}^{N}\widehat{\rho}_{ir}$, where T denotes the number of time periods and $\widehat{\rho}_{ir}$ denotes the estimated correlation coefficient between the time-series for regions i and r.

(4), and does not allow for time trends, which means that it does not control for common factors. For this test, the Augmented Dickey-Fuller (ADF) t-statistics are reported. The tests by Pedroni (1999, 2004) do allow for heterogeneous cointegration as well as the possibility to control for common factors by including time trends. For this test, also ADF t-statistics are reported as well as the non-parametric modified Phillips-Perron (PP) statistics that are robust to serial correlation by using the estimator by Newey and West (1987). Also, two tests developed by Westerlund (2005) are conducted, one to test for cointegration in some panels and one for all panels. Both do not require any correction for temporal dependencies.

Most tests reject the null hypothesis of no cointegration between air accessibility and GDP per capita. Only the Pedroni ADF tests fail to reject the null of no cointegration with GDP per capita for medium-sized and small airports. Looking at Fig. 1, GDP per capita and accessibility for small airports indeed seem to be the 'least' cointegrated series, especially after 2009. However, all other tests do support the hypothesis of cointegration, which in a potentially heterogeneous panel could be interpreted as enough of the individual cross-sections having significant test statistics to generate a significant statistic for the whole panel (Baltagi, 2005, p. 255). Therefore, it can be confidently assumed that all air accessibility variables are sufficiently cointegrated with per capita GDP.

3.3.4. *Equilibrium relations and Granger causality*

Provided that air accessibility and GDP per capita are cointegrated, it is possible to estimate long-run equilibrium relationships from Eq. (4). To get to a robust assessment of long-run relationships, several estimators are used. Pooled OLS (POLS) and fixed effects (FE) estimators restrict long-run relationships to be homogenous ($\beta_i = \beta$) and at most allow for heterogeneity through individual intercepts in FE models. Mean Group (MG) estimators estimate Eq. (4) separately for all N cross-sections and average coefficients. This addresses the bias in pooled estimates in the presence of heterogeneity (Pesaran and Smith, 1995). Although estimation by OLS is consistent in MG approaches, the associated standard errors are not reliable in the presence of endogeneity, even under cointegration. This is a likely issue, given the possible reverse causality between air accessibility and GDP. Therefore, also Group-Mean Fully Modified OLS (GM-FMOLS) models are reported, which make non-parametric adjustments to the autocovariances between the variables in a cointegrated relationship to take account of serial correlation and endogeneity (Pedroni, 2001).[7] Finally, not accounting for the presence of cross-sectional dependence (see Section 3.3.1), the above-mentioned estimators will inhibit an omitted variable bias from unobserved common factors. To mitigate this issue, Eq. (4) can be augmented by cross-sectional averages of both the dependent and independent variables yielding the Common Correlated Effects estimators (CCEP for pooled and CCEMG for MG estimators).

To assess causality, the following vector error-correction model (VECM) is formulated:

$$\Delta \ln GDP_{it} = \alpha_{1i} + \eta_{1i}\widehat{e}_{i,t-1} + \sum\nolimits_{p=1}^{K} \delta_{1ip}\Delta \ln GDP_{i,t-p} + \sum\nolimits_{p=1}^{K} \lambda_{1ip}\Delta \ln ACC_{i,t-p} + \varepsilon_{1it} \tag{5}$$

$$\Delta \ln ACC_{it} = \alpha_{2i} + \eta_{2i}\widehat{e}_{i,t-1} + \sum\nolimits_{p=1}^{K} \delta_{2ip}\Delta \ln ACC_{i,t-p} + \sum\nolimits_{p=1}^{K} \lambda_{2ip}\Delta \ln GDP_{i,t-p} + \varepsilon_{2it} \tag{6}$$

where $\widehat{e}_{it}$ represents the residual after estimating the long-run equilibrium relationship in Eq. (4). The coefficient η_i reflects the speed of adjustment to the equilibrium, which, if significant, implies long-run Granger causality running from air accessibility to GDP per capita in Eq. (5) and from per capita GDP to air accessibility in Eq. (6). The Granger representation theorem implies that under cointegration long-run causality must hold in at least one direction (Engle and Granger, 1987). The significance of λ_{ip} indicates short-run Granger causality. The joint significance of η_i and λ_{ip} indicates the presence of 'strong' Granger causality (see also Baker et al., 2015).

Following Canning and Pedroni (2008), Eqs. (5) and (6) are estimated for every region using the Johansen (1988, 1991) maximum-likelihood procedure. It should be noted that individual estimates per region may be somewhat unreliable due to the relatively short time under study.[8] However, in large cross-sections, rejection in a larger number of regions can still be taken as evidence against the hypothesis that there is no causality for the panel as a whole (Baltagi and Kao, 2000; Canning and Pedroni, 2008; Pedroni, 2019). Finally, binary probit models are estimated to make inferences on the type of regions in which air accessibility leads to economic growth.

4. Results

The presentation of the findings follows the two-step empirical approach. First, levels of regional air accessibility and the contribution of smaller airports to that are evaluated. Afterwards, we present the model results regarding the relationship between regional air accessibility and levels of per capita GDP.

4.1. *Contribution of smaller airports to air accessibility*

Fig. 2a displays the distribution of air accessibility across Europe as defined in Eq. (2). Since air accessibility has no real intuitive measurement unit,[9] the pattern can merely be interpreted comparatively. Values have been log-transformed and presented in standard deviations. Note that for these descriptive cross-sectional analyses, we classify airports based on passenger numbers in 2018.

Unsurprisingly, air accessibility is high along the'Blue Banana' corridor running from London to Milan as well as in large urban agglomerations such as Athens, Barcelona, Paris, Stockholm and Warsaw. Lower values of air accessibility are found in more peripheral European regions. These regions include large parts of Central and Eastern Europe, sparsely populated areas in Scandinavia, and parts of the Spanish and French interiors. In short, accessibility appears to be associated with population density and economic prosperity (see also Antunes et al., 2020). This is confirmed in explorative cross-sectional models in which air accessibility is regressed on regional socio-economic characteristics (see Table 5). Higher air accessibility is associated with larger populations, higher densities, higher per capita GDP, lower shares of secondary sector employment and lower unemployment rates. Air accessibility from medium-sized and small airports is less associated with population size and density, and negatively with high-tech employment. Due to a lack of land-side connections, island regions[10] may be expected to have higher levels of air accessibility. This is only confirmed for medium-sized airports. Note that the adjusted R^2 becomes

[7] Alternatively, autoregressive distributed lag (ARDL) models can be used to infer on long-run relationships in cointegrated panels (e.g. Chudik et al., 2015). However, these models usually rely on the assumption of at least weakly exogenous regressors, which is often violated under cointegration (Pedroni, 2019).

[8] However, $T \approx 20$ is acceptable (Eberhardt, 2011) and comparable to earlier studies in this context (e.g. Mukkala and Tervo, 2013; Tolcha et al., 2020; Van de Vijver et al., 2016).

[9] A weighted average over all population centres in a region of the sum of near airport sizes in terms of passengers handled weighted by distance to those airports through a negative exponential function.

[10] In accordance with Eurostat's methodological guide to territorial typologies (Eurostat, 2019), we define an island region as a region consisting entirely of one or multiple islands.

Table 4
Tests for panel cointegration with ln GDP per capita.

	Kao ADF	Pedroni ADF	Pedroni modified PP	Westerlund variance ratio (some panels)	Westerlund variance ratio (all panels)
lnACC_{total}	2.785***	−4.353***	6.814***	2.251**	2.876***
lnACC_{large}	5.722***	−4.038***	6.338***	1.750**	4.346***
lnACC_{medium}	2.759***	1.183	8.650***	5.293***	6.018***
lnACC_{small}	3.650***	0.226	7.925***	2.446***	2.511***

All variables are per capita and demeaned to mitigate strong cross-sectional dependence. The Kao and Pedroni tests have the alternative hypothesis of cointegration in all panels, while Westerlund's tests have the alternative hypotheses of cointegration in all panels or at least some panels. For the Kao and Pedroni tests, the Newey and West (1994) automatic lag selection algorithm is used to correct for serial correlation. **$p < 0.05$, ***$p < 0.01$.

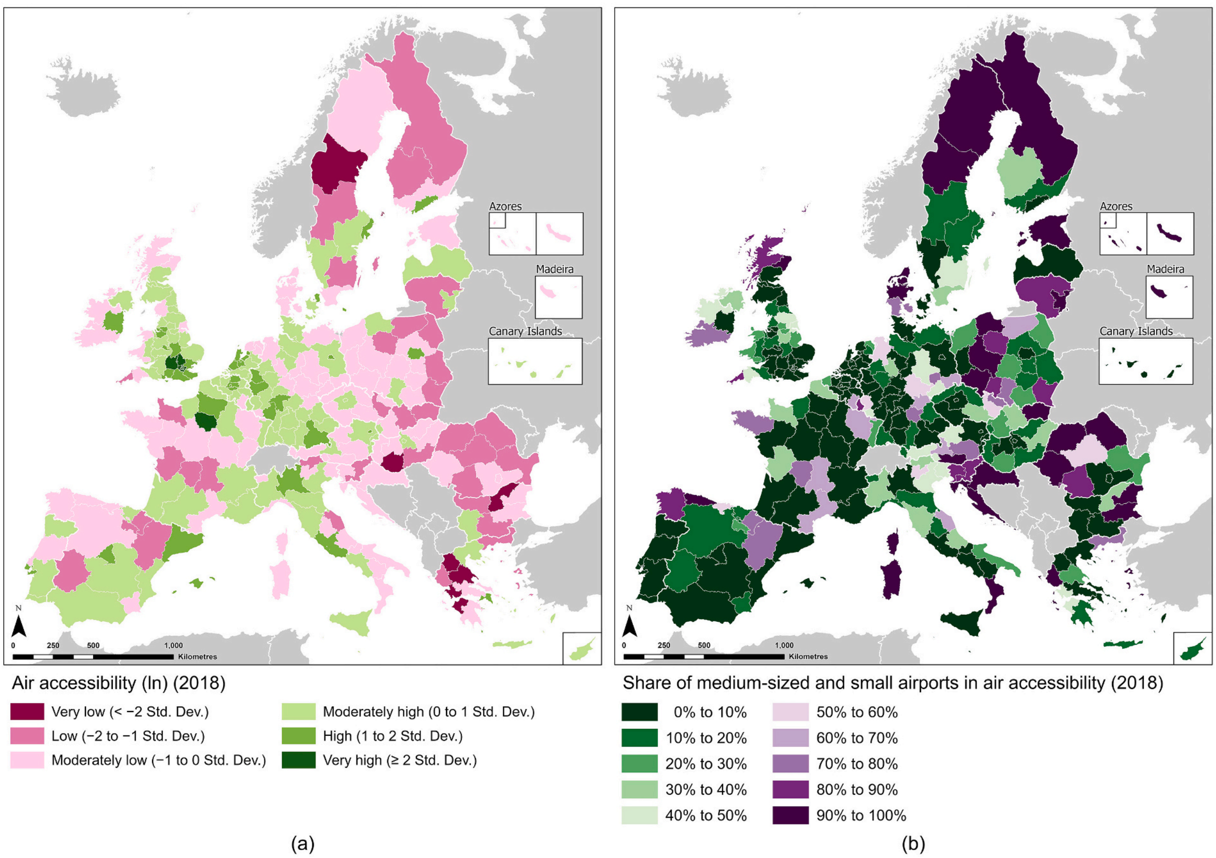

Fig. 2. Absolute levels of air accessibility in Europe (a) and the share of medium-sized and small airports (b).

substantially lower for accessibility provided by medium-sized and small airports, which is indicative of large heterogeneity across the regions involved.

Fig. 2b shows the great disparity across Europe concerning the importance of medium-sized and small airports in providing air accessibility. Mimicking the results of Redondi et al. (2013), the contribution of smaller airports to accessibility is typically low. The median of the share of medium-sized and small airports combined is 13%, and at the 75th percentile, more than half of air accessibility is provided by medium-sized and small airports. Only at the 95th percentile, more than half of air accessibility is provided by small airports. Put differently, providing a different perspective, 70 European regions inhabiting 96 million people (19% of the total population in the sampled regions) rely primarily on these smaller airports for air accessibility of which 14 regions inhabiting 13 million (3% of the total population in the sampled regions) people mainly on small airports.

Table 6 presents the results of an explorative fractional probit regression explaining the share of small airports in air accessibility. Density and employment in high-tech are the most salient factors that are associated, negatively, with the importance of small airports in air accessibility. This emphasizes the potential relevance of small airports for remote and less developed regional economies.

4.2. Air accessibility and regional economic development

4.2.1. Long-run relationships

Table 7 shows the results for the long-run cointegrating Eq. (4) on the relationship between all air accessibility variables and per capita GDP. Looking at air accessibility in total, all coefficients are positive and significant, with elasticities ranging from 0.089 (CCEP) to 0.250 (GM-FMOLS). Across all estimators, large airports exhibit the strongest links with GDP per capita, with elasticities ranging from 0.059 to 0.340. The association is weaker for air accessibility from medium-sized (between 0.003 and 0.165) and small airports (between 0.022 and 0.079). Note that air accessibility per capita is used to correct for scale effects.

The choice of the preferred estimator can be based on the overall predictive performance based on RMSE values, the way parameter heterogeneity is allowed and how effective cross-sectional dependence is eliminated. Looking at the homogeneous approaches, POLS is rejected in favour of FE in all cases following *F*-tests. Also, RMSE values are

Table 5
OLS regressions on levels of air accessibility.

Dependent variable: air accessibility (ln)	All airports	Large airports	Medium-sized airports	Small airports
Population (ln)	0.462***	0.516***	0.099	0.003
	(0.093)	(0.173)	(0.230)	(0.209)
Population density (ln)	0.534***	0.900***	0.514***	−0.096
	(0.059)	(0.114)	(0.144)	(0.135)
GDP per capita (ln)	0.675***	1.123***	1.188**	1.023**
	(0.206)	(0.387)	(0.497)	(0.461)
Tertiary education share (%)	0.013	0.005	0.037	0.030
	(0.009)	(0.017)	(0.022)	(0.021)
Employment share in manufacturing (%)	−0.085***	−0.086*	0.028	−0.009
	(0.023)	(0.044)	(0.057)	(0.053)
Employment share in high-tech (%)	0.061	0.004	−0.335***	−0.287***
	(0.043)	(0.079)	(0.105)	(0.096)
Unemployment rate (%)	−0.044***	−0.030	−0.176***	−0.082**
	(0.017)	(0.031)	(0.044)	(0.037)
Island region (dummy)	0.492	0.923	1.071**	−0.844
	(0.302)	(0.586)	(0.804)	(0.855)
Constant	−1.211	−8.764*	−3.523	0.687
	(2.378)	(4.442)	(5.798)	(5.349)
Number of observations	257	255	249	253
F-test	62.3***	31.4***	8.82***	2.91***
Adjusted R^2	0.657	0.489	0.202	0.057

Estimation year is 2018. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 6
Fractional probit regression on the share of small airports in air accessibility.

	Small airport share (%)
Population (ln)	−0.141
	(0.106)
Population density (ln)	−0.342***
	(0.083)
GDP per capita (ln)	−0.327
	(0.280)
Tertiary education share (%)	0.014
	(0.011)
Employment share in manufacturing (%)	0.038
	(0.025)
Employment share in high-tech (%)	−0.146***
	(0.057)
Unemployment rate (%)	0.005
	(0.019)
Island region (dummy)	−0.541
	(0.343)
Constant	5.254
	(3.232)
Number of observations	257
Wald-χ^2	67.7***
Log pseudo-likelihood	−63.562
Pseudo-R^2	0.141

Estimation year is 2018. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

substantially higher for the POLS models. The CCEP models yield much smaller coefficients but the highest model fit statistics of the homogeneous estimators, indicating an upward bias in the FE models from the omission of common factors. Unexpectedly, the CCEP approach does not seem to mitigate cross-sectional dependence further in the large airport model. However, the average cross-sectional correlation coefficients are low in all homogeneous models.

Turning to the heterogeneous models, which account for potential heterogeneity across regions, the GM-FMOLS estimators yield slightly higher coefficients than the unadjusted models. This may mean that the potential bias in the regular MG estimator is not substantive. Yet, the CD-test statistics and corresponding average correlation coefficients for both of these estimators are high. Just as in the homogeneous models, the CCE estimator reports much smaller coefficients but also smaller CD-statistics with negligible average cross-sectional error correlation coefficients. Also, RMSE values for the CCEMG are generally the lowest across all models. This makes the CCEMG the most reliable estimator, yielding an overall elasticity between air accessibility and per capita GDP of 0.106. For air accessibility from large airports, this elasticity is higher with a value of 0.179, while for medium-sized and small airports this long-run relationship drops to 0.033 and 0.022, respectively. This drop is likely related to an on average lower network quality offered by smaller airports since elasticities should be equal for all airport types if they, on average, would offer equal network quality and would only differ in size. This underlines that not only the presence of an airport but also the amount and quality of available connections are related to regional economic development (Florida et al., 2015).

Fig. 3 shows the long-run relationship between air accessibility and GDP per capita based on the CCEMG estimate for different values of γ. In general, the relationship becomes exponentially weaker when a smaller catchment area is assumed (i.e. a higher γ). This is related to the intuition that the relationship between air traffic and GDP per capita occurs at some distance from the airport and underlines the need to look beyond administrative units. This pattern is particularly evident for small airports which include recently commercialized, in some cases former military, airports, located at more peripheral locations that entail low costs in order to attract LCCs (Behnen, 2004). The, on average, more peripheral location of smaller airports is highlighted by a greater average distance from urban concentrations (see Table 1). For large airports, the relationship also becomes weaker as the assumed catchment area becomes smaller, but at a lower rate. This may reflect the fact that larger airports are often more centrally located and more likely to attract economic activities directly related to the airport. For medium-sized airports, the relationship remains fairly stable across the range of parameters tested.

4.2.2. *Causality results*

Table 8 presents the percentage of regions for which the null hypotheses of no Granger causality are rejected at the 10% level. Rejection in a larger number of regions can be taken as evidence against the hypothesis that there is no causality in any region. The proportion of regions rejecting the null is tested against the expected proportion of 10% when using this significance level (i.e. type I error).

The results suggest causality in both directions. Yet, it should be noted that only in 12% of regions bidirectional strong Granger causality is identified. This indicates that usually, one direction of causality is dominant in a region. Causality running to GDP per capita is accepted for airports in general at the 10% level. This evidence is strongest for large airports and weaker for medium-sized and small airports, although the latter two categories do not significantly differ in this respect. This is an indication that the strength of causality running to economic growth may not be linearly related to airport size, again underlining that size-based classification of airports may be problematic for developing regional economic policy. Evidence for causality running from economic growth to air accessibility is more substantive. Far more regions show causality in this direction, especially for medium-sized and small airports. Regarding the time horizon in which effects occur, causal effects manifest themselves mainly in the long run, especially in the direction from air accessibility to economic growth. This indicates that the economic effects of air traffic need time to materialize.

It should be noted that in addition to GDP per capita, absolute GDP levels could also increase air accessibility due to the size of the market and the mere availability of funds to expand airport facilities or attract airlines. Replication of the causality analyses has indeed shown that absolute GDP levels can increase levels of regional air accessibility. However, the regions with a significant causal relationship based on absolute GDP levels are largely the same as in our analyses using GDP

Table 7
Estimation results for the long-run relationship between air accessibility and GDP per capita.

Dependent variable: GDP per capita (ln)	Homogeneous			Heterogeneous		
	POLS	FE	CCEP	MG	GM-FMOLS	CCEMG
All airports						
β	0.162***	0.234***	0.089***	0.210***	0.250***	0.106***
	(0.003)	(0.004)	(0.006)	(0.013)	(0.001)	(0.014)
CD-test	3.73***	−0.52	1.83*	273.1***	95.1***	7.22***
$\overline{\rho}$	0.004	−0.001	0.002	0.324	0.113	0.009
RMSE	0.319	0.074	0.044	0.040	0.031	0.025
Large airports						
β	0.059***	0.330***	0.220***	0.272***	0.340***	0.179***
	(0.001)	(0.011)	(0.010)	(0.015)	(0.002)	(0.019)
CD-test	8.33***	2.79***	10.9***	281.0***	426.7***	3.61***
$\overline{\rho}$	0.011	0.004	0.015	0.382	0.580	0.005
RMSE	0.292	0.069	0.037	0.040	0.020	0.023
Medium-sized airports						
β	0.032***	0.064***	0.003	0.136***	0.165***	0.033***
	(0.002)	(0.005)	(0.005)	(0.011)	(0.001)	(0.009)
CD-test	27.0***	20.4***	4.26***	277.4***	33.7***	6.26***
$\overline{\rho}$	0.033	0.025	0.005	0.340	0.041	0.008
RMSE	0.411	0.093	0.044	0.042	0.033	0.025
Small airports						
β	0.045***	0.046***	0.022***	0.063***	0.079***	0.022***
	(0.003)	(0.002)	(0.002)	(0.005)	(4.7E-4)	(0.004)
CD-test	17.2***	16.9***	3.17***	277.3***	411.1***	3.64***
$\overline{\rho}$	0.021	0.020	0.004	0.334	0.495	0.004
RMSE	0.413	0.091	0.038	0.041	0.054	0.024

All variables are per capita. All models include time trends. $\overline{\rho}$ denotes the average cross-sectional correlation coefficient of the Pesaran (2004) CD-test. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

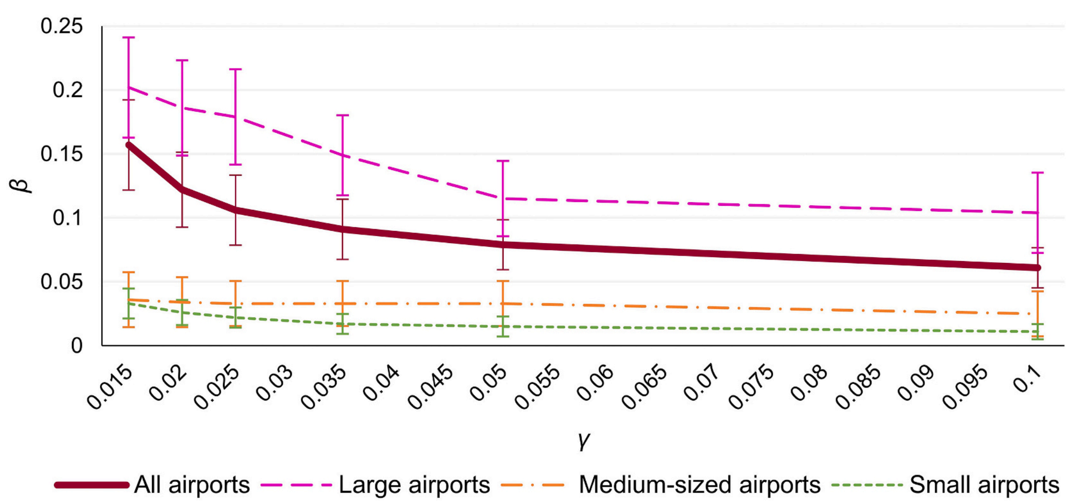

Fig. 3. Long-run elasticity between air accessibility and GDP per capita for various values of γ.

per capita. This is confirmed by ϕ[11] values that indicate a strong correspondence between the results (ϕ > 0.5 in all cases) (Cohen, 1988). Specifically, ϕ equals 0.75, 0.71, 0.84, and 0.69 for large, medium-sized, small, and all airports, respectively.

As with evaluating the long-run equilibrium relationships, the presence of causality may be sensitive to different values of γ in Eq. (3). Comparing our baseline situation using $\gamma = 0.025$ with the minimum and maximum values evaluated in this study, 0.015 and 0.1, yield largely the same regions exhibiting significant causality for both directions and all airport classes (see Table 9). This suggests that the identification of a causal link between air accessibility and per capita GDP is less sensitive to assumptions about the size of airport catchment areas than the strength of this link.

Table 10 presents the results of binary probit models to explore for which types of regions the causality runs from accessibility to GDP per capita. First, the model corrects for the level of GDP per capita since this may lead to a lower probability of additional economic growth, consistent with the expectation of diminishing returns from transport infrastructure. This can be confirmed in general and applies especially to large and small airports, but is not apparent for medium-sized airports.

[11] $\phi = \sqrt{\frac{\chi^2}{N}}$

Table 8
Share of regions rejecting the null of no Granger causality at the 10% significance level.

	Accessibility → GDP/capita			GDP/capita → Accessibility		
	Strong	Short-run	Long-run	Strong	Short-run	Long-run
All airports	34.4%***	9.1%	41.2%***	50.0%***	26.9%***	53.6%***
	(1.812)	(1.812)	(1.812)	(1.812)	(1.812)	(1.812)
Large airports	37.7%***	12.5%	49.4%***	42.3%***	24.3%***	36.0%***
	(1.941)	(1.941)	(1.941)	(1.941)	(1.941)	(1.941)
Medium-sized airports	32.4%***	9.4%	42.3%***	53.6%***	10.9%	59.6%***
	(1.843)	(1.843)	(1.843)	(1.843)	(1.843)	(1.843)
Small airports	32.2%***	13.7%*	41.1%***	59.6%***	14.8%**	67.0%***
	(1.826)	(1.826)	(1.826)	(1.826)	(1.826)	(1.826)

Under the null hypothesis of no causality in all regions, the share of regions rejecting this hypothesis at the 10% significance level is expected to be 10% with a standard error of $30/\sqrt{N}$. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Second, the role socio-economic characteristics is assessed. Denser regions are more likely to leverage accessibility for per capita GDP growth, which may reflect the role of accessibility in facilitating agglomeration economies. To capture imbalances in inbound/outbound flows, the annual number of stays in tourism accommodations serves as a proxy for incoming rather than outgoing air traffic and generally exhibits a positive impact, particularly regarding large airports. Considering employment, only for medium-sized airports we find evidence that regions with high employment in high-tech may benefit from air accessibility, although we do find that a higher share of employment in manufacturing is generally negatively associated with the leveraging per capita GDP growth from accessibility in all other models. This confirms that the link between passenger movements and GDP per capita is more evident for the service industy than for goods-related employment (Brueckner, 2003; Zhang and Graham, 2020). Medium-sized airports do seem to have the potential to positively impact the economy when unemployment levels are higher, while this relationship is reversed for small airports. This underlines the heterogeneity in the nature and function of airports in regional economies.

Finally, the regression explores the characteristics of accessibility for the causality with GDP per capita. Potential competition with rail transport negatively impacts the probability for causality running from air traffic to economic growth, except when considering large airports. The absolute level of total air accessibility is negatively associated with a positive impact on GDP per capita for medium airports. This links to the notion of diminishing returns. In regions where air accessibility is already high, an expansion of a medium-sized airport may not bring many benefits, possibly because this class typically includes secondary airports operating point-to-point networks. The standard deviation of annual changes in air accessibility is included, as it can be expected that high fluctuations of traffic are a less stable base for economic growth. This is indeed confirmed in the medium and small airport models, where fluctuations more likely translate into significant changes in the connectivity provided.

Table 9
Strength of the association (ϕ) between regions exhibiting strong Granger causality for different values of γ compared to the baseline results.

	Accessibility → GDP/capita		GDP/capita → Accessibility	
	$\gamma = 0.015$	$\gamma = 0.1$	$\gamma = 0.015$	$\gamma = 0.1$
All airports	0.83	0.68	0.76	0.57
Large airports	0.94	0.71	0.83	0.73
Medium-sized airports	0.88	0.83	0.88	0.86
Small airports	0.84	0.69	0.84	0.63

Table 10
Binary probit models explaining causality from air accessibility to per capita GDP.

Dependent variable: strong Granger causality from air accessibility to GDP per capita (dummy)	All airports	Large airports	Medium-sized airports	Small airports
GDP per capita (ln)	−1.087***	−0.791**	0.264	−0.972***
	(0.382)	(0.397)	(0.357)	(0.371)
Population density (ln)	0.473**	0.355*	0.324*	0.525***
	(0.188)	(0.191)	(0.185)	(0.186)
Nights spent at tourist accommodations (ln)	0.160*	0.233**	0.082	−0.011
	(0.089)	(0.094)	(0.090)	(0.087)
Tertiary education share (%)	−0.001	−0.002	−0.016	0.012
	(0.015)	(0.017)	(0.015)	(0.015)
Employment share in high-tech (%)	0.095	0.001	0.148**	−0.058
	(0.070)	(0.076)	(0.072)	(0.069)
Employment share in manufacturing (%)	−0.116***	−0.090**	−0.039	−0.148***
	(0.043)	(0.045)	(0.038)	(0.043)
Unemployment rate (%)	−0.002	0.009	0.062**	−0.079***
	(0.028)	(0.034)	(0.028)	(0.028)
Rail infrastructure (km/km^2)	−0.611**	−0.456	−0.679**	−0.553*
	(0.287)	(0.295)	(0.290)	(0.289)
Mean absolute level of total air accessibility (ln)	−0.033	−0.044	−0.221**	−0.044
	(0.102)	(0107)	(0.103)	(0.102)
Accessibility fluctuation (Std. Dev. of $\Delta \ln ACC$)	−0.029	−0.044	−0.085**	−0.026***
	(0.025)	(0.050)	(0.035)	(0.009)
Mean large airport share (%)	−0.162	−0.144	0.204	0.034
	(0.350)	(0.351)	(0.333)	(0.345)
Island region (dummy)	−0.510	−0.084	−0.871	−0.341
	(0.667)	(0.886)	(0.625)	(0.751)
Constant	1.235	−0.233	−7.375*	3.204
	(4.315)	(4.533)	(4.220)	(4.282)
Number of observations	244	216	238	244
LR-χ^2	53.9***	43.2***	46.6***	53.9***
Log-likelihood	−124.4	−118.5	−120.0	−124.4
Pseudo-R^2	0.178	0.154	0.163	0.180

Estimation year is 2018. Standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

5. Conclusions

Airports are often portrayed as drivers of economic growth, even though the empirical evidence on this relationship is inconclusive still. There appears to be considerable heterogeneity in the roles airports play in regional economies. This study addresses this heterogeneity by explicitly distinguishing between major airports and smaller airports. This distinction is salient since smaller airports in particular are often believed to have a substantive impact in peripheral economies. In addition, imminent institutional changes towards restricting state support for such airports spark the question of what would be the 'loss' for an economy should a small airport be closed. We take a careful approach in trying to establish causality between the accessibility provided by types of airports and per capita GDP growth since improved accessibility can be both a driver and a result of economic growth. Importantly, we also allow catchment areas of airports to overlap since regions may be served by multiple airports within or outside the administrative borders. Not taking this into account would inflate the relative weight of individual airports, particularly of smaller airports within the catchment area of a larger one. In this approach, we can also parcel out the relative importance of smaller airports in a region's total accessibility.

On the whole, the analysis shows that the role of smaller airports in total accessibility is limited. In the region at the median, 13% of total accessibility is provided by medium-sized and small airports. Only at the 75th percentile do these airports provide more than half of total regional accessibility. At the same time, offering a somewhat different perspective, this means that 70 European regions inhabiting 96 million people rely primarily on small and medium-sized airports for air accessibility of which 14 regions that together inhabit 13 million people mostly on small airports. The importance of smaller airports in total accessibility follows population density, with the most thinly populated regions being dependent on small airports in particular. There is, however, considerable heterogeneity across regions in the share of smaller airports in total accessibility.

The long-run elasticity between air accessibility and per capita GDP is estimated at 0.106 and is higher for large airports (0.179) than for medium-sized (0.033) and small airports (0.022). This may be due to differences in network quality, as elasticities could be expected to be equal if all airport classes would on average offer equal network quality and only differ in size. Data on the specific dimensions of connectivity may shed light on which aspects of network quality are important for the relationship between air accessibility and GDP per capita.

There is also considerable heterogeneity in the causal relation between accessibility and GDP growth, which is in line with the conflicting empirical evidence available. Taking a helicopter view, however, the results favour an interpretation in which the level of accessibility provided by airports follows GDP development rather than the other way around. For large airports, we find the clearest indications that there is a self-reinforcing process with causality running in both directions. For smaller airports, the results strongly suggest that the accessibility provided by these airports is derived from economic growth rather than the other way around. Only in lagging but densely populated regions with potential for agglomeration economies and a relatively low share of manufacturing employment do we see some indication of the small airport being a pillar of economic growth.

Where does this leave us regarding the policy narrative that regional airports are an important part of the regional economy and as such justify the support of regional and national governments? At face value, the conclusion would be that state aid is not justified in most regions, given that air accessibility of people and firms only slightly decreases if an airfield shrinks or even closes down. Suitable alternatives are typically right around the corner. Mirroring this, the effect of smaller airports on the economy is not evident. In fact, smaller airports are rather sustained by a certain development level. Larger airports do seem to benefit the economy. This suggests that airports need to operate at a certain scale before they provide spillover effects to the wider economy. Although on average, the justification for support for small airports seems thin, we do find considerable regional heterogeneity in the importance of airports for accessibility and their impact on the economy alike. Particularly in remote areas, these airports fulfil an important role both in ensuring air accessibility and, albeit tentatively, in facilitating the economy. It stands to reason that this is reflected in the position of governments in trying to sustain such airports. The heterogeneity across regions and its potential implications for policies suggest that a fruitful avenue for further research would be to improve our understanding of the features of regions and airports in connection to their role in regional economies. In addition to the understanding that there may be region-specific economic considerations that warrant support for regional airports, there may of course also be other arguments for sustaining an airport even if its exact purpose in terms of ensuring accessibility or facilitating economic growth is limited. These could include image effects, considerations regarding accessibility equity, or the goal to spread passengers so as not to overburden a nearby hub airport.

In the end, whether to financially support small airports is a political choice. This paper maintains that such choices need to be made in the context of the network of connections available and not by considering single airports. With this in mind, the loss of accessibility, as well as the economic damage of closing a small airport, are likely limited.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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