ERASMUS UNIVERSITEIT ROTTERDAM

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Examining Passenger Traffic Growth Dynamics:

A Comparative Panel Data Analysis of U.S. Primary and Secondary Airports

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Abstract

Due to growing environmental concerns, policy debates concerning the expansion of airport capacity hold a prominent position on the global political agenda, including those that relate to Schiphol Airport. Therefore, the main focus of this research is to determine whether the growth trajectories of U.S. hub airports, based on passenger traffic, exhibit conditional beta-convergence as a function of various endogenous and exogenous variables. In total, 128 primary and secondary airports are examined during the 2018-2019 timeframe. The empirical analysis primarily employs a panel data approach, with random effects and an instrumental variable. According to this analysis, an increase of one percent in a hub's annual enplanements results in the decrease of its annualized passenger growth rate with 0.013 percentage points on average at a 5 percent significance level. However, the three robustness checks confirm that this conditional convergence rate can not be interpreted as causal. Nonetheless, the findings of this research can translate in to strategic policy implications, such as those that stimulate the development of small hubs to reduce congestion present at larger hubs in the U.S.

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1. Introduction

On a global scale, the growth of both primary and secondary airports is on the upswing. However, in the current political climate in many countries, the expansion of airport capacity is at the forefront of the policy debate. Similarly in the Netherlands, as in June 2022 the cabinet decided that an improved balance must be found between economic interests and the quality of the living environment around Schiphol Airport. A crucial moment in time, as the Dutch government introduced the mandatory adoption of the 'Balanced Approach' procedure by Schiphol Airport, in line with European legislation and regulation. This implementation of this procedure means that Schiphol has become subject to operational restrictions, and has to limit its total flight movements in the upcoming years. Thus, concerns over noise nuisance, emissions, public health, and overall liveability in the vicinity of Schiphol Airport have led to the reduction of its capacity (Ministerie van Infrastructuur en Waterstaat, 2023). Nevertheless, pressure from the U.S. government threw a spanner in the works, resulting in the announcement of the Dutch government that Schiphol's capacity will not be scaled down. The underlying reason is summarised by the reaction of the trade association and lobby group ‘Airlines for America (A4A)’, as it argued that the introduction of operating restrictions violates the aviation treaty between Europe and the U.S. (Van Der Parre, 2024).

In fact, the study by Oum et al. (2006) shows that substantial differences emerge from varying forms of ownership and institutional structures on the performance of airports in terms of their productive efficiency, operating profits and user charges. In line with the governance issues surrounding Schiphol Airport, the results from this paper suggest that non-American airports with a government majority ownership are significantly less efficient than privately owned and operated airports. In general, the literature on this topic comes to the common conclusion that there are significant differences in the efficiency of airports, which consequently affects their growth trajectories. Overall, research indicates that large airports are more efficient than smaller airports, suggesting that airport operations are subject to economies of scale (Hooper & Hensher, 1997; Martín et al., 2009; Yoshida, 2004).

Large airports are also referred to as primary airports in professional terms, and facilitate more than 10,000 passenger boarding’s each year. Small airports are commonly referred to as secondary airports, facilitating between 2,500 and 10,000 passenger boarding’s per year (Federal Aviation Administration, 2022). As argued by Button et al. (1999), there is no discrete or legal definition of a hub airport. However, in practice, they are classified as airports with a large majority of the flights operated as part of a regional network by an air carrier. Alternatively, according to the Federal Aviation Administration's definition (2022), hubs receive 0.05 percent or more of the annual U.S. commercial enplanements. Nonetheless, it is generally agreed upon by the literature that two types of passengers use these large airports; those that transit when changing aircrafts and those residing at a hub airport city. As a result, hubs compete with each other for both types of passenger traffic demand, combined with their supply of airport services. This interplay of supply and demand not only determines hub premiums, but could also potentially explain the growth trajectories of airports, regardless of their size or ownership (Button et al., 1999). While the literature reviewed on this topic mostly relates to the U.S. aviation industry, the insights gained from these papers can provide valuable extrapolations for understanding similar patterns at European airports, such as Schiphol airport. This assumption is supported by the paper of Button (2009), which outlines the chronological impact and progress of the 'Open Skies' agreements between the United States and Europe. In accordance with the definition of the U.S. government, Open Skies agreements involve negotiations regarding the regulation of passenger and cargo services on international routes between the U.S. and other countries (U.S. Department of State, n.d.). The longstanding Open Skies agreements with Europe have also created a transatlantic aviation market that has been shaped by the regulatory elements of these agreements. As a result, both the European and U.S. aviation industries are thoroughly interlinked, a fact further reinforced by the effects of globalisation (Button, 2009). Also, it should be noted that due to the lack of research and data on behalf of the European aviation industry, this research will mainly focus on U.S. airports.

As foundational to our understanding, Button et al. (1999) argue that hub airports drive economic growth, but together with airlines additionally capitalize on the existing benefits of local economies. Their analysis, which examines high-technology employment growth in cities around hub airports, underscores the fact that increased passenger traffic positively impacts employment growth in Metropolitan Statistical Areas (MSA's). As outlined in the literature, previous studies approached airport growth through the lens of efficiency and input-output cost structures, or employment dynamics. However, this thesis aims to bridge this gap by investigating the growth rates of hub airports as a function of both metropolitan demand and supply-side variables. This methodological approach could contribute to our understanding of airport growth dynamics, and addresses a significant knowledge gap within this scientific field of air transport economics. In particular, this approach examines the empirical concept of conditional beta-convergence based on passenger traffic, which describes the convergence of passenger growth rates of smaller hubs approaching those of larger hubs over time. Moreover, this research will contribute to the body of economic literature on this topic, as there is quite a limited amount of research available that examines airport growth trajectories on the basis of conditional beta-convergence, or even considers demand-side mechanisms in this context. Furthermore, the findings of this research could provide relevant informative insights to the global political policy debates regarding airport capacity expansion, including those concerning Schiphol Airport. Therefore, the main research question of this thesis is as follows:

"Do U.S. secondary airports grow faster than U.S. primary airports in terms of passenger traffic, and what factors contribute to this growth disparity during the timeframe of 2018-2019?"

In order to answer the main research question, a panel data regression analysis with random effects will be employed, using data from 2018 till 2019. To address the endogeneity concerns associated with the Average Fares variable, this analysis is conducted using an instrumental variable approach. The hub size classification of each airport in this dataset will serve as the instrumental variable, thus mitigating potential biases in the regression results. The inclusion of this instrumental variable aims to isolate the exogenous variation in average airline fares driven by the varying hub sizes. Consequently, this analysis is considered to have a causal interpretation of the results under the assumption that average airline fares do not correlate with other excluded confounding factors that affect passenger growth rates, after incorporating several control variables. In summary, the presence of conditional beta-convergence in the growth trajectories of U.S. hub airports is examined through the mechanisms of metropolitan demand characteristics and supply-side endogenous variables.

2. Related Literature

2.1 Theoretical Framework

The theoretical framework of this research is based upon the general concept of beta-convergence, which is essential in examining whether secondary airports in the U.S. converge towards the growth rates of primary airports over time. As explained by Sala-I-Martín (1996), two definitions of convergence are commonly assumed in the academic literature, that is, beta-convergence and sigma-convergence. In general, beta-convergence describes the process in which the economies of poor countries tend to grow faster than rich countries' economies in terms of per capita income on the long term. Sigma-convergence, on the other hand, relates to a larger scale, and occurs when the differences in per capita income among a group of similar economies decrease over time. These concepts have their origins in the fundamental Solow model, which has been extended by Mankiw et al. (1992) with the inclusion of human capital as a significant driver of economic growth. Initially, the Solow growth model only incorporated the rates of saving, population growth and technological progress as exogenous variables, in combination with labor and capital inputs. However, as demonstrated in the results of their paper, the authors find supporting evidence for the hypothesis that the growth rate of capital is driven, among other things, by the accumulation of human capital.

In practice, economies differ in their initial levels of human capital, population growth, labor inputs, saving rates et cetera. Therefore, the Solow model predicts that countries, each with their unique economies and correspondingly varying characteristics, will converge to their own individual steady states in terms of per capita income. Furthermore, this model also assumes that the growth rate of an economy is positively related to the distance from its steady state, which implies that poor economies will grow faster than rich economies only under the assumption that they are currently not in their steady state. In classical literature, this phenomenon is referred to as '*conditional beta-convergence'*, and is in line with the predictions of the Solow model. In contrast, *'absolute convergence'* takes place when all countries converge to the same steady state, which implies that there will be a general level of per capita income globally (Sala-I-Martín, 1996).

Whereas the findings of the Mankiw et al. (1992) and Sala-I-Martín (1996) papers relate to a national scale, the paper of Barro et al. (1991) underlines that the principles of convergence also apply to a sub-national scale, specifically to U.S. states. The model of Barro et al. (1991) examines the convergence of personal income and Gross State Product (GSP) across U.S. states between 1880 and 1988, and finds that within- and between-region conditional convergence rates are similar. This effect is further stimulated when labor mobility and the flow of technological advances from rich to poor U.S. states are taken into account. Thus, this paper supports the notion that conditional convergence mechanisms could explain the cross-state differences with respect to their economic growth patterns.

While the conclusions of the studies reviewed earlier either revolve around national or regional level, Rodrik (2012) shifts the focus to industry-specific convergence. In particular, the author shows that labor productivity levels in manufacturing industries across 118 countries are advancing at the same absolute convergence rate. On firm level, the convergence rate largely depends on technological advancement, as proposed by Barro et al. (1991). In their model the steady state output per effective worker depends on parameters of technology, which includes natural resources and governmental policies. In addition, Rodrik (2012) suggests that the slower pace of convergence in some manufacturing industries in terms of GDP per worker can be attributed to firm-specific circumstances that hinder the structural reallocation from non-converging to converging activities. As a result, countries with high growth trajectories typically succeed in implementing policies that mitigate market and government failures which prevent this structural transformation, and are directly aimed at enhancing this reallocation within firms.

This review of the concept of convergence provides a framework for understanding the growth patterns of primary and secondary airports over time. Overall, the discussed seminal papers conclude that convergence ratios approach approximately two percent in general (Barro et al., 1991; Mankiw et al., 1992; Rodrik, 2012; Sala-I-Martín, 1996). In the context of this research, this fact offers a crucial benchmark for examining whether the concept of conditional convergence applies to the growth trajectories of hub airports in the U.S.

2.2 Empirical Research

This theoretical framework is extended with examining the dynamics of airport growth in further detail. At the core of this framework are the growth trajectories of airports as a function of metropolitan demand and supply-side factors. The interplay between these two aspects has led to an increased level of competition between airports. This trend is particularly reinforced by the liberalisation of the global aviation industry, as put forward by Hooper and Hensher (1997). As a result, there has been an emphasis on measuring performance from a cost-efficiency perspective in order to quell this competition as an airport. The cost-efficiency of airports can be calculated by the Total Factor Productivity (TFP) method. Overall, this TFP method is a function of supply-side inputs weighted by their cost shares, and outputs weighted by their cost elasticities. Using the TFP method, the authors were thus able to show that larger Australian airports exhibit lower output-adjusted TFP levels in comparison to smaller Australian airports with higher output-adjusted TFP levels. This finding provides evidence that the overall efficiency levels are converging among the examined airports.

This finding contradicts the results of Martín et al. (2009), as this paper demonstrates that large airports benefit relatively more from economies of scale than small airports in Spain. The cause of these divergent results can be substantiated by methodological differences of the papers. For instance, Martín et al. (2009) criticise the TFP method, for not taking into account the decomposition of changes in technology. Therefore, the authors adopt a stochastic frontier analysis that incorporates the cost structures of input prices and a proxy of technological development as a function of time. According to their interpretation, larger airports achieve increasing economies of scale as they can afford to outsource ancillary activities by specialised parties. Moreover, in similarity to Martin et al. (2009), the TFP method is also found to be deficient by Yoshida (2004). This paper applies the Endogenous-Weight TFP method, which compares each observation with the theoretical values of input and output indices to measure the endogenous production transformation. The findings of Yoshida (2006) are in line with those of Martín et al. (2009), as they prove that activities of larger Japanese airports show strong increasing returns to scale compared to smaller Japanese airports.

The growth of the aviation industry as a function of demand factors is outlined in the study of Graham (2000), in which the author underpins that the growth trajectories of airports are subject to consumers' ability and willingness to travel. However, growing environmental concerns restrict the infrastructural expansion of airport capacity. The resulting implications encourage heavier competition among airports aimed at leveraging demand-side factors, as these now have become the crucial determinants of air travel participation. In other words, airports are competing on prices that reflect the purchasing preferences (i.e. price elasticity) of their consumers. In response to this kind of competition, airports are also setting their sights on optimising access cost and time as argued by Pels et al. (2003). The paper aims to provide insight into the passenger sensitivity to these factors, and carries the main conclusion that access time is the one of the most important determinants in the choice strategy of consumers, especially for business travellers. Therefore, the implication that follows is for airport managers to invest in faster access modes, although such improvements could lead to rent-seeking behaviour of airlines, as airline fares will raise as a result of the increased demand.

The impact of fares charged by U.S. airlines on airline and passenger revenues is further examined by Van Dender (2007). The paper finds that the regional concentration of airports within the operational area of an origin airport, and its share of international departures, are both of major importance in determining average airline fares. Furthermore, different forms of regulation and privatization affect these charges as well, as demonstrated by the varying policies of the studied European airports by Bilotkach et al. (2012). Based upon three airports that moved away from *'ex post regulation'*, including Schiphol airport, the paper concludes that airports subject to this type of regulation have lower aeronautical charges. To clarify, ex post regulation is a regulatory mechanism which involves price monitoring and the threat of re-regulation by authorities. In addition, the authors also show that large European airports appear to systematically charge higher airline fares, or so-called hub premiums. Furthermore, in the same vein as Bilotkach et al. (2012), different types of ownership have diverging effects on the performance of European and Asia-Pacific airports, as put forward by Oum et al. (2006). However, an important distinction arises as there is no significant difference in efficiency between publicly and privately owned North American airports. Nonetheless, the European and U.S. aviation industries share similarities with respect to airline fares, as Ciliberto and Williams (2010) observe that hub premiums are increasing in the distribution of ticket fares at American airports as well. Moreover, the paper presents evidence that hub premiums are heavily influenced by the control of gates and the degree of congestion, that is, the ratio of departures over the amount of boarding gates. In fact, both factors create a scarcity of leasable gates, which is a barrier to entry for airlines and limits the demand for airport services.

The demand for airport services is a key driver of the structural development of regional airline networks and employment growth on the long-term, according to Irwin and Kasarda (1991). In particular, the growth of the airline network alters the competitive position for producer-service employment in metropolitan areas, an occupation which primarily entails firms selling services to other firms. Intuitively, this effect is further stimulated in metropolitan areas that are relatively decentralized, in other words that do not face congestion in terms of limited infrastructure growth. These findings are further supported by the work of Button et al. (1999), which states that the economic prosperity of cities is highly dependent on local air transport systems. To quantify these local benefits, their research reveals that the presence of a hub airport significantly increases the regional high-technology employment with 12,000 jobs on average in U.S cities.

Thus far, his theoretical framework has outlined several underlying mechanisms of airport growth. However, Open Skies Agreements (OSA's) have led to changes in the competition regime of the aviation market as well, as these agreements have the main objective to shift the 'international aviation system based on competition among airlines with minimum government regulation', according to Micco and Serebrisky (2006). The authors determine that air cargo freight costs decrease by 9 percent on average five years or more after the signing of an OSA, for (medium-) high income countries. In relation to OSA's and the international aviation traffic between the U.S. and Europe, the paper of Whalen (2007) demonstrates that the passenger capacity of airlines operating between the U.S. and Europe significantly increases after signing Open Skies treaties. The latter fact is entirely due to the expansion of immunized alliances on routes, which refer to highly integrated partnerships between airlines that are granted antitrust immunity by government authorities. This immunity allows airlines to coordinate on scheduling, pricing, and revenue sharing as if they were merged. In conclusion, understanding how OSA's affect various factors in the aviation industry provides informative insights into the overall implications for the formation of airport policies.

3. Data and Methodology

3.1 Data

The sample used in this analysis consists of different types of airports. Furthermore, the classification of primary and secondary airports in this research is based upon the concept of 'major airports', which corresponds to so-called 'hub airports' in the United States. Specifically, airports that are identified as 'Large Hubs' receive 1 percent or more of the annual U.S. commercial enplanements, as defined by the Federal Aviation Administration (FAA) (2022). In total, there are 30 airports that could be classified as large hubs, or primary airports, within the timeframe of 2018-2019. Secondary airports are selected from the categories of 'Small and Medium Hubs'. These airports are defined as airports receiving 0.05 to 0.25 percent and 0.25 to 1.0 percent of the annual U.S. commercial enplanements, respectively (Federal Aviation Administration, 2022). During the 2018-2019 period, there were 32 medium hubs and 74 small hubs present. This number of classified hubs is drawn from the 'CY 2019 Passenger Boarding Data' and 'CY 2018 Passenger Boarding Data' FAA documents and Excel databases. To clarify, this research deviates from the standard criteria due to the significant differences in passenger volumes and distinct characteristics of secondary airports, which are often oriented towards private commercial services. As a result, alternative definitions of primary and secondary airports are applied in this analysis.

Information on behalf of the total annual amount of passengers, or enplanements, of each airport is obtained from these aforementioned FAA documents and Excel databases. This data is extracted from the 'Air Carrier Activity Information System' (ACAIS) FAA database (Federal Aviation Administration, 2023). The total amount of airports included in these FAA databases amounts to 136 airports. However, it is worth mentioning that there is no matching American Community Surveys (ACS) data available for 8 airports located in either Puerto Rico, or on American islands, on behalf of their metropolitan areas. These airports are therefore excluded from the analysis, resulting in a sample size of 128 airports per year, see Appendix Table A1. This exclusion has led to a reduced amount of 67 small hubs and 31 medium hubs in total, with the amount of large hubs remaining constant. Furthermore, to obtain annual data on behalf of average airline fares, the 'Average Domestic Airline Itinerary Fares' database of the Bureau of Transportation Statistics is consulted. This database consists of unadjusted average airline fares for round-trip purchases grouped by origin airport. Averages are calculated using a 10 percent sample of all airline tickets for U.S. carriers, and include the total ticket value plus additionally charged non-optional taxes and fees (Bureau of Transportation Statistics, 2024). For the 2018-2019 timeframe, these average airline fares are extracted to generate the Average Fares variable.

In regards to the control variables that relate to employment and household income in this analysis, the ACS databases are used. The ACS, issued annually by the U.S. Census Bureau, are databases that consist of the continuously collected data on social, economic, housing and demographic characteristics of U.S. citizens (US Census Bureau, 2024b). In addition, the 'Metropolitan Statistical Area Population Estimates and Estimated Components of Change' database from the same U.S. Census Bureau is consulted to construct the Population Growth variable. To incorporate the GDP Growth variable, real GDP per capita data is derived from the Bureau of Economic Analysis (BEA), specifically from the 'Gross Domestic Product by County and Metropolitan Area' database. The exogenous variables obtained from the U.S. Census Bureau and BEA databases will serve as controlling factors in the regressions. These variables entail key features of the airports' market environment and capture passenger demand for departures. Moreover, these control variables are all grouped on MSA level, which is supported in two ways. First, the methodologies of Van Dender (2007) and Button et al. (1999) align closely with this research, and both employ exogenous variables at MSA level. Second, Irwin and Kasarda (1991) examine the relationship between the structural expansion of the airline network and employment growth in MSA's, in line with the study of Button et al. (1999). The authors argue that the growth of the air transportation market has led to the creation of local advantages in metropolitan areas, due to the reduction of long-distance economic interaction. In other words, changes in exogenous factors that drive passenger demand for airport services are most effectively studied at MSA level, as a result of the presence of localized externalities.

Overall, the following control variables are included: average airline fares, mean household income, real GDP per capita growth, population growth, employed population, and the sectoral concentration of the employed population, see Appendix Table A2. Finally, it should be noted that the selected databases theoretically allow for an examination of the 2018-2022 timeframe, in contrast to the covered period of 2018-2019 in this research. This deliberate restriction aims to mitigate the distorting effects of COVID-19, and ensures a more accurate analysis that is unaffected by the impact of the global pandemic.

3.1.1 Descriptive Statistics

This section presents the descriptive statistics of the variables under study, in order to summarize their main characteristics and provide insight into the dataset structure. Appendix Table 3 shows the descriptive statistics of all variables, in which the three continuous variables are presented in both logarithmic and untransformed form. The untransformed form offers an understanding of the actual variability and distribution across the sample. Appendix Table 4 displays the correlation matrix which includes the dependent variable Passenger Growth Rate, the main independent variable of interest Log(Enplanements), and the control variables. According to Appendix Table 4, no substantially high correlation coefficients are present within the sample. Nonetheless, a Variance Inflation Factor (VIF) analysis is conducted, to rule out any potential multicollinearity issues. In general, VIF values greater than five indicate the presence of multicollinearity. The VIF values are displayed in Appendix Table 5, and support the conclusion that there is no indication of multicollinearity within the independent variables.

In regards to the characteristics of the continuous independent variables, Appendix Table 3 shows that the annual amounts of enplanements and average fares vary considerably, indicating heterogeneity among airports. For example, the average amount of enplanements is 6,849,481 passengers, with a standard deviation of 9,870,897 passengers. In the same manner, the Average Fares variable also contains a wide range of values, as the average fare across airports included in the sample is 361.201 dollars, with a standard deviation of 74.338 dollars. Moreover, it appears that similar conclusions can be made for the Mean Household Income variable. With an average of 90,381.71 dollars and a standard deviation of 21001.33 dollars, the mean household income varies considerably across MSA's. However, the maximum value of 172,126 dollars signals a certain income threshold being present among ACS respondents, as it is common knowledge that there are families earning more than 172,126 dollars on an annual basis in the United States. Thus, in order to effectively address the substantial variation in their distributions, the logarithmic form is applied to the continuous variables.

Figure 1 shows the histogram of the endogenous variable Average Fares, to further examine the distribution of this variable. This histogram illustrates that the distribution of the Average Fares variable is so-called '*fat-tailed*'. This distribution form suggests that the values cluster around the mean of 361.201 dollars, with significant extreme values being present in the tails of the distribution, resulting in substantial variability across the observations. For instance, the small proportion of average fares near the minimum value of 114.651 dollars indicates the existence of outliers on the lower end of the distribution. Moreover, the absence of observations in the approximate interval of 180 till 210 dollars verifies that average fares within this interval are non-existent in the dataset. Furthermore, this research primarily focuses on the concept of conditional convergence regarding passenger traffic of hub airports. Therefore, Figure 2 displays the scatterplot with the dependent variable Passenger Growth Rate and independent variable Enplanements. The fitted line within this scatterplot indicates that there is a negative correlation between passenger growth rates and annual enplanements, for the sample of airports within the 2018-2019 timeframe. This finding supports that the concept of conditional convergence applies to this analysis.

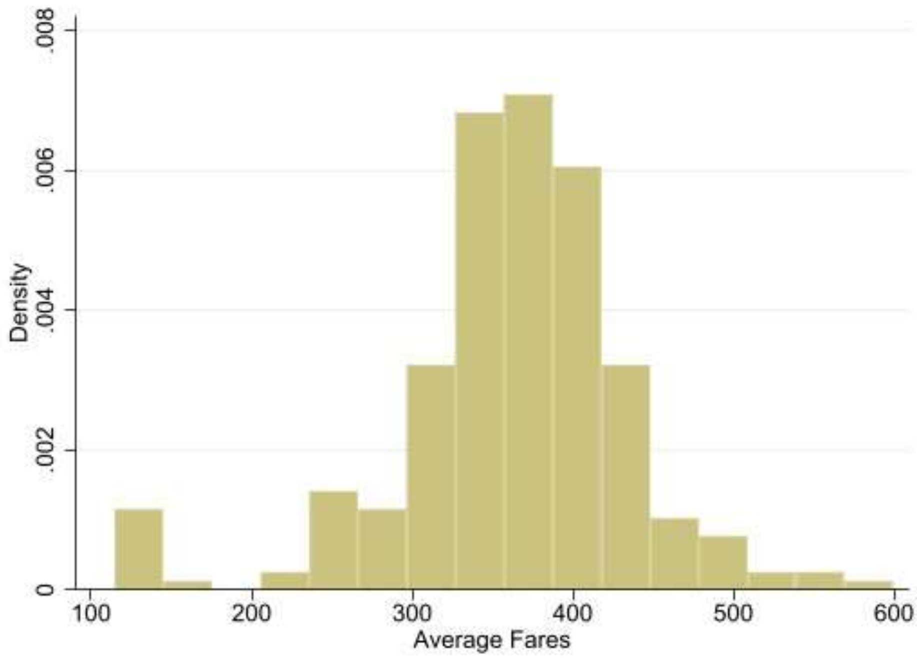

Figure 1: Histogram Average Fares Variable

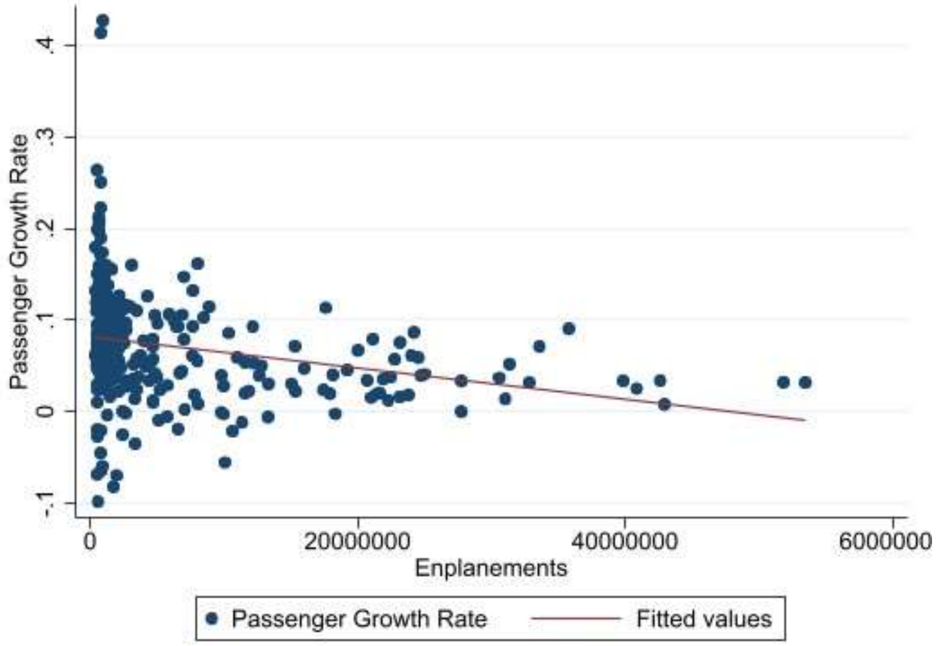

Figure 2: Scatterplot Passenger Growth Rate and Enplanements Variables

3.2. Methodology

In order to examine if the concept of conditional convergence applies to the passenger growth rates of hub airports in the 2018-2019 timeframe, the methodology employed in this research mainly adopts a panel data regression analysis. In particular, this methodology examines the relationship between endogenous and exogenous factors and the passenger traffic patterns of hub airports, referred to as airport growth. The panel data regression analysis is performed using a random effects approach, which assumes that airport-specific heterogeneous effects are uncorrelated with the independent variables. Moreover, this allows for both time-invariant and time-variant effects to be incorporated in the results. Thus, to comprehensively examine whether conditional convergence applies to this research, different regression models are evaluated under different assumptions. Initially, a panel data regression model without the instrumental variable (IV) Hub Size is performed, followed by a second panel data regression model which does incorporate the IV. In contrast to the two preceding models, the third panel data model employs the untransformed form of the Log(Average Fares) variable. The latter change is driven by the observation that the Hub Size instruments exhibit stronger explanatory power in the first-stage in this manner. Lastly, two cross-sectional IV regression models with random effects covering the timeframe of 2018-2019 will be evaluated to examine the robustness of the other models' results.

Overall, this methodological approach ensures that the dynamics of airport growth can be investigated thoroughly, because the exogenous variables are grouped at MSA level per airport. The regression equation that will be estimated in the second-stage of the first two panel data models is defined as follows:

$$Passenger\ Growth\ Rate_{it} = \beta_0 + \beta_1 Log(Enplanements)_{it} + \beta_2 Log(AverageFares)_{it}$$
$$+\beta_3 Log(MeanHouseholdIncome)_{it} + \beta_4 Employment_{it} + \beta_5 GDPGrowth_{it} +$$
$$\beta_6 PopulationGrowth_{it} + \beta_7 SelfEmployed_{it} + \beta_8 ServiceSectors_{it} + \beta_9 PublicSectors_{it}$$
$$+ \beta_{10} ManualSectors_{it} + \beta_{11} TradeSectors_{it} + \beta_{12} Year2018_t + \varepsilon_{it} \ (1)$$

In this estimated model, the dependent variable Passenger Growth Rate is the annualized growth rate in terms of total passengers, or so-called enplanements, of airport 'i' and year 't'. Furthermore, the variable Log(Enplanements) denotes the annual logarithmic amount of enplanements of airport 'i' and year 't'. Thus, the coefficient β_1 is of main interest as it enables to determine whether the hypothesis of conditional convergence holds for all observations. In other words, coefficient β_1 measures the conditional beta-convergence rate. The endogenous variable Log(Average Fares) contains the average airline itinerary fares of airport 'i' and year 't'. The other variables, ranging from coefficient β_3 till β_{12}, are exogenous control variables that are included to remove some of the confounding factors and are also listed in Appendix Table 2. Lastly, ε_{it} represents the error term.

In line with the paper of Sala-I-Martín (1996), if the coefficient $\beta_1<0$, it indicates that the data exhibits conditional beta-convergence. This means that if the annual enplanements of the growing airports increase, their passenger growth rates will decline and approach to zero as the airports reach their individual steady states. As discussed before, airports with initial lower levels of annual enplanements are further removed from their own individual steady states, which results in growth trajectories with higher passenger growth rates and diminishing returns to expansion. This phenomenon is empirically proven by the paper of Irwin and Kasarda (1991). The authors argue that U.S. secondary airports operating within decentralized MSA's were able to expand their structural capacity as a result of the lack of congestion and opportunities for infrastructure growth during the 1950-1980 timeframe. In contrast, primary airports quickly reached their capacity limits during this timeframe, which can be attributed to the high degree of congestion within their MSA's. Building upon these findings, this research will therefore explore the dynamics of airport growth through another lens. While Irwin and Kasarda (1991) primarily investigate employment growth on the basis of the structural airline network expansion, this research shifts the focus to airport growth driven by underlying mechanisms of metropolitan demand characteristics and supply-side endogenous factors.

The latter objective can be accomplished through conducting three different panel data regression models. As discussed before, the first model that will be presented is a regular panel data regression model that employs equation (1) without the incorporation of the instrumental variable. This model provides an understanding of the baseline correlations between the dependent and the independent variables. However, potential biases in these estimates remain as a result from the endogenous Log(Average Fares) variable. The reason as to why this variable is considered to be endogenous stems from the fact that there is a two-way causality between the average airline fares and the passenger growth rates, at any given airport. This means that average airline fares affect passenger growth rates, and vice versa. In general, this interplay is academically referred to as *'reverse causality'*. Without the incorporation of the IV, the estimates will be biased and inconsistent, because the endogenous variable is correlated with the error term in equation (1). In response to this endogeneity issue, the second panel data regression model employs equation (1), but also includes the instrumental variable. This IV is the dummy variable Hub Size, which contains the hub size classification of each hub airport, categorized as small, medium, or large.

The selection of Hub Size as an IV can be divided according to three main requirements, which are all met. First, the IV is of relevance as it is likely to be highly correlated with the endogenous Log(Average Fares) variable. This correlation stems from the fact that larger hubs typically have different pricing mechanisms than medium or small hubs. This observation is proven by different seminal papers discussed before, such as by that of Ciliberto and Williams (2010), which demonstrates that the hub premiums of U.S. hubs are increasing in airline ticket fares. For instance, their results show that the hub premium is less than 10 percent for hubs located in the tenth percentile of the average fares distribution, and almost 25 percent for hubs in the 90th percentile. Thus, the varying hub sizes have their own distinctive casual effects on average airline fares, which needs to be accounted for. Secondly, these effects are assumed to affect the dependent variable Passenger Growth Rates only through the Average Fares variable. In other words, it is only through the mechanisms surrounding the Average Fares variable that the hub sizes influence the dependent variable, meaning that there is no direct relationship present. This observation is also empirically supported by Ciliberto and Williams (2010), who show that the sizes of hub airports affect the number of passengers through the supply of leasable gates. If a relevant airline increases its share of controlled gates by 10 to 30 percent, airline fares increase by 3 percent. However, this process also contributes to airport congestion, resulting in higher hub premiums and slower growth in the number of departing flights. Lastly, the selection of this IV is based on the assumption that it is correlated with the Log(Average Fares) variable but not directly with the error term in the regression model.

With this instrumental variable approach, the endogeneity of the Log(Average Fares) variable is addressed. However, it appears that the untransformed form of the Log(Average Fares) variable enables the instruments to exhibit improved explanatory power, in contrast to the logarithmic form. In other words, the correlation between the IV and the endogenous variable is considerably reliant on the extreme values of the fat-tailed distribution, displayed in Figure 1. This results in the stronger significance of the instruments in the first-stage of this model. In order to examine this observation in further detail, the third panel data regression model is estimated according to the following equation:

$$Passenger\ Growth\ Rate_{it} = \beta_0 + \beta_1 Log(Enplanements)_{it} + \beta_2 AverageFares_{it}$$
$$+\beta_3 Log(MeanHouseholdIncome)_{it} + \beta_4 Employment_{it} + \beta_5 GDPGrowth_{it} +$$
$$\beta_6 PopulationGrowth_{it} + \beta_7 SelfEmployed_{it} + \beta_8 ServiceSectors_{it} + \beta_9 PublicSectors_{it}$$
$$+ \beta_{10} ManualSectors_{it} + \beta_{11} TradeSectors_{it} + \beta_{12} Year2018_t + \varepsilon_{it} \quad (2)$$

To simplify the interpretation of the results, the estimated coefficients are divided by one hundred in the first-stage of this model. Furthermore, random effects models account for random variations across entities over time, meaning that this approach assumes that the airport-specific effects are uncorrelated with the independent variables. Nonetheless, as this research spans the timeframe of two years, the inclusion of the year dummy may identify certain time-invariant patterns that may influence the estimated coefficients in equations (1) and (2). Therefore, the dummy variable Year 2018 isolates possible year-specific fixed effects belonging to the year 2018, such as any economic-, industrial- or policy-related changes. These changes could remain unobserved but still affect the growth trajectories of airports. Through the comparison of the variation of the time-invariant factors of the year 2018 with that of the reference category, the year 2019, these effects no longer have an opportunity to correlate with the error term.

In line with establishing airport growth trajectory patterns, the last two cross-sectional models enable the assessment whether the estimated coefficients exhibit consistency in terms of magnitude, sign and significance in the short-term. Both robustness checks employ equation (2), with the exception of the Year 2018 dummy. To conclude, it is worth mentioning that employing a fixed effects regression approach is unfortunately not feasible in this analysis. The short-term timeframe of this research results in the lack of independent time series variation among airports. Moreover, the hub size instruments can be considered as time-invariant. This hinders the estimation of their respective first-stage effects, with the inclusion of fixed effects, when there is no sufficient amount of observations over time.

3.2.1 Control Variables

Understanding the growth dynamics of primary and secondary airports requires the inclusion of several control variables in the regression analysis, in order to reduce any potential biases put forward by confounding variables. If these confounding variables are not accounted for in the regression analysis, the corresponding estimated results will be biased. In fact, these variables will then still influence the dependent variable Passenger Growth Rates and the independent variable Log(Enplanements). Therefore, to ensure more accurate estimates, exogenous variables that capture metropolitan demand dynamics are also incorporated. Overall, the whole set of control variables in the regression models has the objective to construct an empirical model aimed at understanding the market environment of airports. With respect to the concept of conditional convergence, these control variables function as specific characteristics on which the different initial levels of enplanements are conditioned on. In the spirit of the classical convergence theory of Sala-I-Martín (1996), control variables are effective measures to correctly proxy for the steady states of airports. Within the context of this research, it is thus essential to include economic and demographic control variables. Moreover, the pool of literature which mostly relates to the convergence of per capita income within economies, reports conditional beta-convergence rates of around 2 percent per year in general (Barro et al., 1991; Mankiw et al., 1992; Rodrik, 2012; Sala-I-Martín, 1996). Hence, this approach ensures that the conditional beta-convergence hypothesis can be tested accurately, and also allows to test whether the results are consistent with this general benchmark.

The first set of control variables relates to socio-economic indicators, that collectively capture the demand for airport services, grouped at MSA level. This set consists of the Mean Household Income, GDP Growth and Population Growth variables. The Mean Household Income variable represents the average income level of households within a MSA, based on individuals 15 years old and over with an income (U.S. Census Bureau, 2019). Secondly, the GDP Growth variable measures the real GDP change per capita. Third, the Population Growth variable includes the growth of the resident population on MSA level. Collectively, these indicators drive the demand for departures from airports, as put forth by Van Dender (2007). In particular, passenger demand is higher when the levels of income per capita and population increase at the airport's location, resulting in the proportionate growth of passenger volumes, departing flights and flight frequency. Although the Van Dender (2007) paper is based on data collected between 1998 and 2002, similar findings appear to have emerged earlier in Irwin and Kasarda's (1991) study as well. In fact, the authors argue that population density is positively related to the degree of airline centrality on MSA level, which in turn creates local advantages for airlines in the period from 1950 to 1980. With regard to GDP growth, higher levels of MSA population and per capita income are also associated with increased passenger volumes on routes operated by airlines flying between Europe and the U.S., according to Whalen (2007).

The second set of control variables concerns the employment rates in the MSA's. These are presented both at an aggregated level and by selected occupational industries. The Employment variable represents the aggregate number of employed people over the age of 16, as a percentage of the civilian labor force. In addition, to measure the distinctive impact of certain industries during this analysis, 15 occupational sectors are considered. On the basis of the North American Industry Classification System (NAICS), 13 private sectors emerged from the data of the ACS (U.S. Census Bureau, 2019). These sectors are further grouped together on the basis of similar work-related operational activities, with the objective of reducing their multicollinearity. This transformation is listed in Appendix Table 2, and has resulted in the final set of 7 occupational sectors. In relation to the growth trajectories of airports, Irwin and Kasarda (1991) underscore that the structural expansion of the air transportation network has significantly altered the competitive advantages of MSA's over time, primarily through its positive influence on the employment of ten pooled industries. Furthermore, this effect is larger for the manufacturing and producer services (i.e. selling services to other firms) industries. Therefore, in order to obtain a comprehensive and detailed understanding of the impact of this structural expansion, it is essential to include employment variables both at the aggregate and sectoral level. This methodology is further substantiated by the paper of Barro et al. (1991), since the convergence of per capita income across U.S. states depends upon the correlation between the different income shares of sectors, which in turn results from varying average levels of productivity and the initial levels of per capita income.

4. Results

The main results of this analysis are presented in Table 1. In particular, this table displays the second-stage results of the three panel data regression models, and of the two cross-sectional regression models, respectively. Furthermore, the sectoral employment variables collectively function as a dummy variable in the regression analysis. In this case, the Service Sector variable is excluded from all regression outputs, and serves as the reference category. Therefore, the regression coefficients of the other sectoral employment variables can be interpreted relative to this reference category. In column 1 of Table 1, the results of the panel data regression model without the IV are shown. Similar to the other regression models, this model incorporates robust standard errors to address any potential heteroscedasticity across the standard errors of the estimates. According to the coefficient in column 1, an increase of one percent in a hub's annual enplanements results in the decrease of its annualized passenger growth rate with 0.013 percentage points on average, at a 5 percent significance level. Moreover, this coefficient is significant at a 1 percent significance level.

In relation to the concept of beta-convergence, this finding suggests that the relationship between the annual enplanements and the passenger growth rates of U.S. hub airports exhibits conditional beta-convergence in the short-term. Although the coefficient is smaller than the generally reported convergence rate of two percent with respect to per capita income, it still implies that airports with initial higher levels of annual enplanements are closer to their own individual steady states. This leads to a growth trajectory with diminishing returns to capacity expansion, which is indicated by the negative coefficient of the Log(Enplanements) variable. Nonetheless, it is evident that the estimated results displayed in column 1 are biased due to the endogeneity of the Average Fares variable and by potential omitted variables. Thus, the four succeeding models that include the instrumental variable Hub Size will be analysed, to address the first concern.

The panel data regression with the IV is presented in column 2 of Table 1. According to column 2, an increase of one percent in a hub's annual enplanements results in the decrease of its annualized passenger growth rate with 0.013 percentage points on average at a 5 percent significance level. This convergence rate coefficient is similar to that presented in column 1. This similarity suggests that conditional convergence applies to the growth trajectories of hub airports in the U.S in the short-term. However, the interpretation of these results in column 2 must be approached with caution, due to the important limitations of the IV and potential biases that remain. To reiterate, the random effects approach does not account for airport-specific characteristics or time-invariant effects, which could still influence the growth trajectories over time. Hence, the independent variables are able to be affected by both factors, which implies that any unobserved confounding factors are included in the error term. This fact compromises the causality of the estimated results of column 2, especially as they are based on estimates derived from the first-stage regression results reported in column 1 of Table 2.

To clarify, Table 2 shows the first-stage estimates corresponding to the two panel data and the two cross-sectional IV regression models, respectively. Moreover, the Large Hub Size variable serves as the reference category for the other two hub size categories. In theory, the IV Hub Size is considered to be valid in order to address the endogeneity of the Average Fares variable. In order to empirically substantiate this fact, the joint significance of the Small and Medium Hub Size variables on the other regressors in the first-stage regression corresponding to column 1 of Table 2 is examined through a Wald test. The p-value of 0.000 reported in Table 3 underlines that both variables are jointly significant in explaining the variation of the Log(Average Fares) variable at a 5 percent significance level. Overall, this finding suggests that this IV is a valid instrument to explain the variation in the endogenous variable Average Fares. In addition, the p-value of 0.000 corresponding to the Wald Chi-Squared test reported in column 1 of Table 2, indicates that all control variables jointly have a significant effect on the endogenous variable. Nonetheless, the coefficient of the Small Hub Size variable is not significant in column 1 of Table 2. The latter finding highlights that, holding other factors constant, the individual contribution of the Small Hub Size variable to the variation in the endogenous variable is insufficient, compared to the Large Hub Size and in relation to the other control variables.

Whereas the statistics of the Wald test confirm that both hub size variables exhibit joint significance, the insignificant coefficient of the Small Hub Size corrects this this observation with the fact that individually small hubs are weakly correlated with the endogenous variable. On the other hand, the joint significance therefore builds upon the explanatory power of the Medium Hub Size variable. Logically, this finding can be substantiated on the basis of Figure 1. The Average Fares distribution is fat-tailed, with a dense concentration of values around the mean, along with higher probabilities of extreme outliers. In fact, according to Appendix Table 7, small hubs display the highest variability with regards to airline fares in comparison to the other two hub sizes. This variability may lead to inconsistent correlation, and consequently an unpredictable impact on the endogenous variable. Moreover, the logarithmic form of the Log(Average Fares) variable reduces the skewness of the fat-tailed distribution, leading to the stabilization of the variability. However, this stabilization possibly hinders the IV regression to distinguish the distinct effect of the Small Hub Size in the first-stage in column 1 of Table 2. Therefore, the panel data IV regression with the untransformed form of the Log(Average Fares) variable is presented in column 3 of Table 1.

This issue is further underlined by the first-stage results of this model, reported in column 2 of Table 2. In fact, the higher Wald Chi-Squared statistic as well as the significance of both hub size variables demonstrate the improved fit of the regression model. Furthermore, the Wald Test p-value of 0.000 reported in Table 4 underlines that both hub size variables are jointly significant in explaining the variation of the Average Fares variable at a 5 percent significance level. Overall, this finding confirms that the correlation between the IV and the endogenous variable is predominantly driven by the extreme values of average airline fares. Moreover, the conditional convergence rate in column 3 differs substantially from that in column 2 of Table 1. This difference can be attributed to the varying coefficients of the independent variables between both models. Also, the GDP Growth and Population Growth variables are anticipated to have a positive relationship with the Average Fares variable, as they serve as indicators of metropolitan demand (Bilotkach et al., 2012). However, all coefficients of these variables are negative in the first-stage, contrary to these expectations. In similar vein, whereas Irwin and Kasarda (1991) find a positive correlation between employment and the expansion of the airline network in MSA's, all second-stage coefficients of the Employment variable are negative. Both observations interestingly contradict the general hypotheses of the two papers. In order to test the robustness of these findings in further detail, the two cross-sectional IV regression models spanning the 2018-2019 timeframe will provide more clarity.

The first-stage estimates of both cross-sectional models are displayed in column 3 and 4 of Table 2. The comparison of these estimates enables the assessment whether the control variables exhibit consistency in terms of magnitude, sign and significance in both years. The observable variation with respect to these three factors across all variables denoted in columns 3 and 4 of Table 2 indicates the presence of endogenous estimates, as argued by Bilotkach et al. (2012). Furthermore, each control variable shows large standard errors in both years, which signals that all of the estimated coefficients are subject to a substantial amount of uncertainty. Moreover, the constants of the first-stage vary significantly. This fact suggests that there are baseline differences in the dependent variable Average Fares between both years which are not accounted for by the control variables. Lastly, both F-statistic p-values corresponding to the first-stages of the cross-sectional models are 0.000, thus confirming that all control variables are jointly significant in explaining the variation in the endogenous variable. Nonetheless, the F-statistic values, 5.53 for the year 2018 and 5.23 for the year 2019, are considerably small compared to the rule-of-thumb F-statistic value of 10. Consequently, these statistics confirm the moderate correlation between the independent regressors and the Average Fares variable.

In general, the limitations discussed during this analysis undermine the crucial assumption of the random effects IV regression model. In fact, this approach assumes that there is no unobserved heterogeneity of the hub airports correlated with the independent variables. However, as a result of the limited explanatory power of the control variables, it is possible that unobserved confounders are correlated with the error term in this model, leading to omitted variable bias. This omitted variable bias arises from excluded time-variant and time-invariant factors which do affect the growth trajectories of hub airports. In regards to this bias, the Year 2018 dummy variable has the objective to isolate any time-invariant effects that occurred in the year 2018, and therefore relate to the market environment of the hub airports. Nevertheless, the Year 2018 variable is not significant in both the first- and second-stages of all panel data regression models at a 5 percent significance level. This fact is an indication that the variation belonging to the time-invariant factors of the year 2018 does not significantly differ from that of the reference category, which is the year 2019. On the other hand, the absence of any year-specific effects suggests that no market-specific events have an influence on the estimates of the variables during the 2018-2019 period.

Apart from the concerns which relate to the omitted variable bias, the short-term timeframe together with the relatively small sample size of this research, compromises the internal validity of the results. Hence, no causal conclusions can be drawn from the regression models, due to several important limitations of the random effects approach. Nevertheless, the various joint-significance tests empirically suggest that the set of endogenous and exogenous variables provides a foundation for a conditional convergence analysis in this context.

Table 1: Second-Stage Results of the Log(Enplanements) on the Passenger Growth Rate

	(1) Passenger Growth Rate	(2) Passenger Growth Rate	(3) Passenger Growth Rate	(4) Passenger Growth Rate	(5) Passenger Growth Rate
Log (Enplanements)	-0.013*** (0.004)	-0.013* (0.006)	-0.015** (0.004)	-0.017* (0.007)	-0.013* (0.006)
Log(Average Fares)	0.021 (0.017)	-0.162 (0.146)			
Average Fares			-0.018 (0.028)	-0.056* (0.028)	0.081 (0.054)
Log (Mean Household Income)	-0.003 (0.007)	-0.004 (0.008)	-0.005 (0.007)	-0.004 (0.061)	-0.007 (0.013)
Population Growth	0.408 (0.951)	0.272 (0.842)	0.533 (0.869)	1.353 (0.793)	0.442 (1.158)
GDP Growth	0.277 (0.222)	0.086 (0.273)	0.287 (0.250)	-0.203 (0.358)	1.254* (0.427)
Employment	-0.483** (0.141)	-0.336 (0.236)	-0.416* (0.168)	-0.291 (0.178)	-0.619* (0.225)
Self Employed	0.096 (0.290)	0.182 (0.399)	0.057 (0.310)	-0.208 (0.478)	0.165 (0.575)
Arts And Education Sectors	-0.225 (0.202)	-0.261 (0.317)	-0.253 (0.230)	-0.189 (0.310)	-0.174 (0.300)
Public Sectors	-0.146 (0.094)	0.218 (0.326)	0.020 (0.195)	0.170 (0.199)	-0.453 (0.378)
Manual Sectors	-0.027 (0.158)	0.488 (0.482)	0.175 (0.277)	0.378 (0.302)	-0.373 (0.510)
Trade Sectors	-0.451* (0.189)	-0.405 (0.238)	-0.411* (0.194)	-0.542 (0.324)	-0.253 (0.319)
Year 2018	0.010 (0.007)	0.015 (0.008)	0.012 (0.007)		
Constant	0.650** (0.202)	1.475* (0.735)	0.785** (0.228)	0.824 (0.782)	0.659 (0.350)
Observations	256	256	256	128	128
Wald-Chi Sq Statistic	95.99	53.99	85.59		
Wald-Chi Sq d.f.	12	12	12		
Wald-Chi Sq *p*-value	0.000	0.000	0.000		
F-Statistic				3.29	4.52
F-Statistic d.f.				(11,116)	(11,116)
F Statistic *p*-Value				0.000	0.000

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: First-Stage Regression Results of Log(Enplanements) on the Average Fares variables

	(1) Log(Average Fares)	(2) Average Fares	(3) Average Fares	(4) Average Fares
Log (Enplanements)	-0.040 (0.029)	-0.204** (0.084)	-0.304* (0.131)	-0.064 (0.125)
Log (Mean Household Income)	-0.009 (0.017)	-0.025 (0.060)	-0.597 (0.556)	0.017 (0.124)
Population Growth	-0.412 (1.218)	-0.834 (3.656)	-4.688 (8.720)	-1.203 (5.825)
GDP Growth	-0.940* (0.438)	-3.250* (1.546)	-4.316 (4.077)	-3.341 (3.354)
Employment	0.824 (0.438)	2.044 (1.217)	2.787 (1.772)	1.989 (1.404)
Self Employed	0.538 (0.966)	-0.933 (2.888)	-0.793 (4.704)	-0.182 (4.333)
Arts And Education Sectors	-0.283 (0.750)	-1.740 (2.043)	-3.082 (2.536)	-1.660 (1.979)
Public Sectors	1.963*** (0.410)	5.558*** (1.110)	5.238*** (1.353)	5.931*** (1.243)
Manual Sectors	2.840*** (0.628)	7.693*** (1.663)	7.271** (2.240)	7.725*** (1.848)
Trade Sectors	0.388 (0.611)	0.152 (1.859)	-1.406 (3.251)	-0.580 (2.680)
Year 2018	0.024 (0.016)	0.084 (0.542)		
Small Hub Size	-0.149 (0.080)	-0.508* (0.229)	-0.786 (0.414)	-0.170 (0.383)
Medium Hub Size	-0.122** (0.045)	-0.494*** (0.135)	-0.654* (0.256)	-0.301 (0.237)
Constant	5.240*** (0.864)	4.131 (2.444)	12.898 (7.355)	1.364 (3.192)
Observations	256	256	128	128
Wald Chi-Sq Statistic	125	150		
Wald-Chi Sq d.f.	13	13		
Wald Chi-Sq *p*-Value	0.000	0.000		
F-Statistic			5.53	5.23
F-Statistic d.f.			(12,115)	(12,115)
F-Statistic *p*-Value			0.000	0.000

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Hub Size Dummy Wald Test in IV Regression First-Stage with Log(Average Fares)

Test Summary	Chi-Squared	Chi-Squared d.f.	*p*-Value
Log(Average Fares)	53.48	2	0.000

Table 4: Hub Size Dummy Wald Test in IV Regression First-Stage with Average Fares

Test Summary	Chi-Squared	Chi-Squared d.f.	*p*-Value
Average Fares	36.43	2	0.000

5. Discussion

The analysis presented in this paper employed different regression models to examine whether the concept of conditional convergence can be applied to the growth trajectories of hub airports. In particular, the main focus of this research revolves around the issue of whether secondary airports grow faster than primary airports in terms of passenger traffic in the U.S. during the timeframe of 2018-2019. Despite the varying methodological approaches employed by the regression models, each is constrained by similar limitations that challenge drawing causal inferences from their respective results. The main pitfalls are reverse causality, omitted variable bias, and selection bias, which can cause spurious associations in this analysis.

As argued before, the correlation between the Average Fares and the Passenger Growth Rate variables is expected to suffer from reverse causality. In fact, this phenomenon has been demonstrated by Bilotkach et al. (2015), as this paper proves that European low-cost airlines can effectively increase load factors through adjusting their fare intervals. In this study, the term 'load factor' refers to the ratio of passengers to the capacity of the low-cost carrier's aircraft. Thus, due to volatile aggregate demand for airline services, airlines respond with a dynamic capacity pricing approach, generally referred to as yield management. In regards to this analysis, this fact can lead to biased and inconsistent estimates, because it is unclear whether the independent variable Average Fares causes changes in the dependent variable Passenger Growth Rate, or vice versa. Moreover, population growth is an endogenous characteristic of employment rates in MSA's, as put forward by Irwin and Kasarda (1991). The authors argue that changes in the population generally align with changes in the labor force across MSA's, which implies that the correlation between the Employment and Population Growth variables is likely to be highly collinear in this research. Once more, this may distort the inference of causal relationships, and result in incorrect conclusions.

Furthermore, there could be selection bias present, which arises from the exclusion of American islands from the sample due to the unavailability of ACS data on behalf of their metropolitan areas. In addition, although the data retrieved from the ACS is collected on the basis of legal obligation and random selection, the validity of the respondents' answers can be questioned still, due to the reliance on self-reported information. The latter can be subject to multiple inaccuracies, such as measurement errors, privacy concerns or inaccurate subjective responses. Taken together, the exclusion of the islands and the internal validity concerns regarding the ACS data, compromise the external validity of the research sample. Thus, the estimates could be biased, as they are based upon a non-representative sample of the American population, which in turn limits the extrapolation of the results.

Furthermore, the empirical evidence of conditional beta-convergence may still suffer from omitted variable bias, if the sectoral production functions of industries differ significantly and consistently from each other over time. If so, these heterogenetic production functions will be positively correlated with the per capita initial income levels of MSA's, and would enter as part of the error term. In regards to hub airports, this omitted variable bias leads to the bias of the Log(Enplanements) variable towards zero. This stems from the fact that the airports' initial levels of annual enplanements are correlated with the variability in the levels of production productivity of their respective MSA's (Mankiw et al., 1992). Unfortunately, random effects regression models are not able to control for such excluded time-invariant characteristics, or other time-varying confounders. If these factors are correlated with the independent variables, this results in endogenous estimates. The presence of this issue is signalled by the relatively small Wald-Chi Squared and F-statistic values corresponding to the regression results. This implies that the explanatory power of the independent variables is not adequate enough to handle the variance in both the Passenger Growth Rate and the Average Fare variables.

This shortcoming also relates to the IV, as it appears that the significance of the Small Hub Size variable is insufficient in comparison to the Large and Medium Hub Size variables. Although the relative proportion of the Small Hub Size variable amounts to 52,34% according to Appendix Table 6, this dominance does not translate in to significant correlation with the endogenous variable. As Ciliberto and Williams (2010) warned, interpreting results using average airline fares can be misleading, because their distribution is not symmetrical. This skewed distribution is also influenced by the local market power of larger hubs. Their market dominance systematically leads to higher hub premiums being charged, especially in the absence of competitive pressures of other local hubs (Van Dender, 2007). Therefore, it is possible that this environment limits the high number of small hubs in their ability to set hub premiums consistently. Moreover, the complex nature of this market environment requires managers of small hubs to adopt a yield management approach, in order to maintain a competitive advantage. This market externality could explain the weakness of the Small Hub

Size variable, as these hubs may exhibit unpredictable extreme variability in terms of their fare structure, according to Appendix Table 7. In contrast, medium and large hubs appear to charge consistent hub premiums.

In light of endogenous control variables, the reviewed literature contends that several others are of interest when examining this research topic. For example, Van Dender (2007) points out that the aggregation of volume related variables challenges the distinction between hub effects from airline concentration effects. In order to resolve this issue, the author proposes that further research should acknowledge the average airline fares per destination or the enplanements per airline for any given airport. Moreover, the inclusion of more supply-side variables, such as measures of airport congestion (e.g. control of gates), would improve the internal validity of this research. Nonetheless, it is unfeasible to include all time-varying and time-invariant variables that could serve as mechanisms of airport growth within the scope of this study. But, even if all relevant control variables were to be included in this analysis, certain drawbacks would still arise from the kind of variation that random effects models account for. In accordance with the findings of Bilotkach et al. (2012), important exogenous variables, such as GDP and population growth, are likely to display insignificant coefficients in combination with panel data structures. This problem originates from the limited availability of within- and between-entity variation which random effects models build upon.

Within the context of this research, the short-term orientation combined with the discussed problems, prevents the conclusive examination of long-term passenger traffic and airline fare patterns, and eventually conditional beta-convergence. Therefore, future studies should first and foremost strive to employ long-term oriented analyses, to circumvent the methodological pitfalls posed by the two-year timeframe of this study. In combination with the incorporation of more relevant control variables, the robustness and generalizability of the results alongside the explanatory power of the IV will then improve. Moreover, this approach would allow for a more comprehensive understanding of the underlying drivers of passenger growth rates, especially if it accounts for heterogeneous time-invariant differences between airports through an additional fixed effects regression analysis. In contrast to random effects regression models, fixed effects models are particularly effective in mitigating the effects of endogeneity, as they control for airport-specific effects over time. The isolation of these effects is essential, to distinguish whether the results are driven by airport-specific idiosyncrasies and to rule out any potential omitted variable bias. In general, the implementation of these methodological refinements offers future studies the opportunity to infer tailored implications for effective policy design with regards to the growth trajectories of hub airports.

6. Conclusion

This research examines the growth trajectories of hub airports on the basis of metropolitan demand characteristics and supply-side endogenous variables. In particular, this research investigates the concept of conditional beta-convergence, which describes how the growth trajectories of small hubs will catch up with those of larger hubs, as all airports approach their individual steady states over time. According to the empirical analysis, an increase of one percent in a hub's annual enplanements results in the decrease of its annualized passenger growth rate with 0.013 percentage points on average at a 5 percent significance level. However, as demonstrated by the three IV regression models that employ the untransformed form of the Log(Average Fares) variable, this finding can not be considered as robust. The latter can be attributed to the different conditional convergence rates of these three models, while they also underline the issue that the control variables do not exhibit consistency in terms of magnitude, sign and significance over the years. Moreover, the small Wald-Chi Squared and F-statistic values indicate the presence of endogeneity within the results in the first- and second stages. Together, these factors provide compelling evidence that the results may be biased and inconsistent. Although the relationship between the Passenger Growth Rate and the Log(Enplanements) variables exhibits significance in all regression models, the estimated rate of conditional convergence can therefore not be interpreted causally.

Nonetheless, the negative correlation between passenger growth rates and annual enplanements, shown in Figure 2, supports the notion that the concept of conditional convergence still applies to hub airports. Whilst the overall methodology needs further refinement to prove this causally, the results of this study suggest that secondary airports are indeed growing faster than primary airports in terms of passenger traffic in the U.S during the timeframe of 2018-2019. Furthermore, the applicable convergence rate within this field of research is significantly smaller than the general convergence rate of two percent with respect to per capita income. Regardless, the existing literature on airport growth based on passenger data remains quite limited. In addition, it also primarily focuses on endogenous supply-side input factors, while overlooking important demand-side mechanisms. Hence, future studies should focus on incorporating all relevant supply- and demand-side indicators in their empirical models. Next, in order to determine which convergence ratio is most applicable with respect to hub airports in the U.S., establishing growth patterns on the long-term is essential. In regards to proper estimation techniques, fixed effects regression models offer an advantage over random effects models. To improve our understanding of airport growth dynamics, fixed effects regression models are able to control for airport-specific effects that may influence the development of their respective passenger traffic patterns.

The implications following from improved methodologies can translate in to strategic policy and planning implications for U.S. hub airports. For instance, the formation of national policy can focus on stimulating the development of small hubs, to reduce congestion at larger hubs if conditional beta-convergence applies. On airport level, identifying critical supply- and demand-side factors can help construct enhanced resource allocation strategies. Finally, understanding the distinct characteristics of different hub sizes enables policy regulations to be tailored according to their size. In conclusion, similar future studies could provide relevant informative insights to the global political debates relating to airport capacity expansion, including those concerning Schiphol Airport.

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8. Appendix

Appendix Table A1: List of All Airports Included in the Sample

Albany International	Harrisburg International	Pensacola International
Albuquerque International Sunport	Hartsfield - Jackson Atlanta International	Philadelphia International
Asheville Regional	Hector International	Phoenix Sky Harbor International
Atlantic City International	Hilo International	Phoenix-Mesa Gateway
Austin-Bergstrom International	Huntsville International-Carl T Jones Field	Piedmont Triad International
Baltimore/Washington International Thurgood Marshall	Indianapolis International	Pittsburgh International
Bill and Hillary Clinton National/Adams Field	Jackson-Medgar Wiley Evers International	Portland International
Billings Logan International	Jacksonville International	Portland International Jetport
Birmingham-Shuttlesworth International	Joe Foss Field	Punta Gorda
Blue Grass	John F Kennedy International	Raleigh-Durham International
Bob Hope	John Glenn Columbus International	Reno/Tahoe International
Boise Air Terminal/Gowen Field	John Wayne Airport-Orange County	Richmond International
Bradley International	Kahului	Roberts Field
Buffalo Niagara International	Kansas City International	Rogue Valley International - Medford
Burlington International	Laguardia	Ronald Reagan Washington National
Charleston AFB/International	Long Beach /Daugherty Field/	Sacramento International
Charlotte/Douglas International	Long Island MacArthur	Salt Lake City International
Chicago Midway International	Los Angeles International	San Antonio International
Chicago O'Hare International	Louis Armstrong New Orleans International	San Diego International
Cincinnati/Northern Kentucky International	Louisville Muhammad Ali International	San Francisco International

City of Colorado Springs Municipal	Lovell Field	Santa Barbara Municipal
Cleveland-Hopkins International	Lubbock Preston Smith International	Sarasota/Bradenton International
Columbia Metropolitan	Mahlon Sweet Field	Savannah/Hilton Head International
Dallas Love Field	Manchester	Seattle-Tacoma International
Dallas-Fort Worth International	McCarran International	Southwest Florida International
Dane County Regional-Truax Field	McGhee Tyson	Spokane International
Daniel K Inouye International	Memphis International	Springfield-Branson National
Denver International	Metropolitan Oakland International	St Louis Lambert International
Des Moines International	Miami International	St Pete-Clearwater International
Detroit Metropolitan Wayne County	Midland International Air And Space Port	Syracuse Hancock International
Eglin AFB/Destin-Ft Walton Beach	Minneapolis-St Paul International/Wold-Chamberlain	Tampa International
El Paso International	Myrtle Beach International	Ted Stevens Anchorage International
Ellison Onizuka Kona International at Keahole	Nashville International	The Eastern Iowa
Eppley Airfield	Newark Liberty International	Theodore Francis Green State
Fairbanks International	Norfolk International	Tucson International
Fort Lauderdale/Hollywood International	Norman Y Mineta San Jose International	Tulsa International
Frederick Douglass - Greater Rochester International	Northwest Arkansas Regional	Washington Dulles International
Fresno Yosemite International	Northwest Florida Beaches International	Westchester County
General Edward Lawrence Logan International	Ontario International	Wichita Dwight D Eisenhower National
General Mitchell International	Orlando International	Will Rogers World
George Bush Intercontinental/Houston	Orlando Sanford International	William P Hobby
Gerald R Ford International	Palm Beach International	Wilmington International
Greenville Spartanburg International	Palm Springs International	

Appendix Table 2: Variables List

Variable	Definition	Source
Passenger Growth Rate	The annualized growth rate of annual enplanements for all hub airports in percentage points	The Federal Aviation Administration (FAA) 'CY Year Passenger Boarding' databases
Log(Enplanements)	The logarithmic form of the total amount of annual enplanements for all hub airports	The Federal Aviation Administration (FAA) 'CY Year Passenger Boarding' databases
Log(Average Fares)	The logarithmic form of the annual average airline itinerary fares grouped by origin hub airport	The Bureau of Transportation Statistics (BTS) 'Average Domestic Airline Itinerary Fares' databases
Average Fares	The annual average airline itinerary fares grouped by origin hub airport in dollar cents	The Bureau of Transportation Statistics (BTS) 'Average Domestic Airline Itinerary Fares' databases
Log(Mean Household Income)	The total household income generated by individuals over 15 years old divided by the total number of households within the metropolitan areas of the hub airports in dollars	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database
Population Growth	The estimated values of population change within the metropolitan areas of the hub airports	The U.S. Census Bureau 'Metropolitan Statistical Area Population Estimates and Estimated Components of Change: April 1, 2010 to July 1, 2019' Database
GDP Growth	The annualized rate of real GDP change within the metropolitan areas of the hub airports	The U.S. Bureau of Economic Analysis (BEA) 'CAGDP1 County and MSA gross domestic product (GDP) summary' databases
Employment	The relative number of employed people over 16 years old as a percentage of the civilian labor force within the metropolitan areas of the hub airports	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database

Self Employed	The relative number of workers that are not employed in neither the private nor government sector within the metropolitan areas of the hub airports	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database
Service Sectors	The relative number of workers employed in the finance, insurance, real estate, rental, leasing, professional, scientific, management, administrative, waste management and information sectors	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database
Arts And Education Sectors	The relative number of workers employed in the arts, entertainment, recreation, accommodation and food services sectors	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database
Public Sectors	The relative number of workers employed in the public administration, government, educational services, health care, social assistance, and other services sectors	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database
Manual Sectors	The relative number of workers employed in the agriculture, forestry, fishing, hunting, mining, construction and manufacturing sectors	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database
Trade Sectors	The relative number of workers employed in the wholesale trade, retail trade, transportation, warehousing and utilities sectors	The American Community Survey (ACS) 'ACS 1-Year Estimates Comparison Profiles, Table CP03, 2019' database

Appendix Table 3: Descriptive Statistics

Variables	N	Mean	Std. dev.	Min	Max
Passenger Growth Rate	256	0.070	0.065	-0.099	0.427
Enplanements	256	6,849,481	9,870,897	403,745	53,505,795
Log(Enplanements)	256	14.855	1.329	12.909	17.795
Average Fares	256	361.201	74.338	114.651	599.299
Log(Average Fares)	256	5.862	0.256	4.742	6.396
Mean Household Income	256	90,381.71	21,001.33	8936	172,126
Log(Mean household Income)	256	11.371	0.344	9.098	12.056
Population Growth	256	0.007	0.010	-0.061	0.0377
GDP Growth	256	0.025	0.019	-0.031	0.078
Employment	256	0.610	0.045	0.485	0.736
Unemployment	256	0.046	0.011	0.018	0.105
Self Employed	256	0.058	0.014	0.032	0.104
Service Sectors	256	0.208	0.042	0.113	0.326
Arts And Education Sectors	256	0.335	0.033	0.272	0.471
Public Sectors	256	0.232	0.057	0.137	0.445
Manual Sectors	256	0.169	0.041	0.097	0.296
Trade Sectors	256	0.193	0.023	0.127	0.278

Appendix Table 4: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Passenger Growth Rate	1.000						
(2) Log(Enplanements)	-0.333	1.000					
(3) Log(Average Fares)	0.137	-0.130	1.000				
(4) Log(Mean Household Income)	-0.140	0.198	-0.051	1.000			
(5) Population Growth	0.232	-0.009	-0.130	-0.114	1.000		
(6) GDP Growth	0.186	0.167	-0.186	-0.032	0.442	1.000	
(7) Employment	-0.318	0.363	0.080	0.155	-0.014	0.095	1.000
(8) Self Employed	0.137	-0.075	-0.085	0.030	0.127	0.250	-0.210
(9) Service Sectors	-0.146	0.560	-0.194	0.279	0.117	0.305	0.434
(10) Arts And Education Sectors	0.025	-0.361	-0.142	-0.032	-0.181	-0.178	-0.284
(11) Public Sectors	0.007	-0.207	0.253	0.060	-0.270	-0.159	-0.200
(12) Manual Sectors	0.144	-0.199	0.285	-0.214	0.138	-0.036	0.075
(13) Trade Sectors	-0.046	-0.069	-0.104	-0.163	0.007	-0.164	-0.293
(14) Year 2018	0.109	-0.022	0.017	0.092	0.054	0.066	-0.040

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(8) Self Employed	1.000						
(9) Service Sectors	0.006	1.000					
(10) Arts And Education Sectors	0.046	-0.460	1.000				
(11) Public Sectors	-0.040	-0.138	0.127	1.000			
(12) Manual Sectors	-0.071	-0.426	-0.299	-0.423	1.000		
(13) Trade Sectors	0.002	-0.381	-0.038	-0.132	-0.081	1.000	
(14) Year 2018	0.023	0.005	-0.011	-0.014	-0.040	0.015	1.000

Appendix Table 5: VIF Analysis

Variables	VIF	1/VIF
Log (Enplanements)	1.71	0.585
Log (Average Fares)	1.40	0.712
Log (Mean Household Income)	1.16	0.863
Population Growth	1.39	0.720
GDP Growth	1.49	0.672
Employment	1.49	0.670
Self Employed	1.16	0.860
Arts And Education Sectors	1.66	0.604
Public Sectors	2.07	0.483
Manual Sectors	2.27	0.441
Trade Sectors	1.36	0.737
Year 2018	1.03	0.972

Appendix Table 6: Relative Proportions of the Hub Size Instruments

	Absolute Total	Relative Proportions
Small Hub Size	67	52,34%
Medium Hub Size	31	24,22%
Large Hub Size	30	23,44%
Total Hubs	128	100%

Appendix Table 7: The Distribution of Average Fares Sorted by Hub Size

Hub Size	N	Mean	Std. dev	Min	Max
Small Hub Size	134	348.36	48.33	240.35	456.06
Medium Hub Size	62	338.82	43.12	267.28	450.53
Large Hub Size	60	377.30	91.96	114.65	599.30