Airport Business Practices and Excess Capacity

Abstract

Excess capacity poses a persistent challenge for airports as they often encounter lumpy capacity in the short run. The excess capacity is primarily influenced by factors such as uncertain demand, airline competition, and the market structure of the airport industry. However, airport business practices also account for this issue. This study investigates the impact of airport use agreements and governance forms on excess capacity, using a two-stage semiparametric model. Our analysis incorporates data from 59 U.S. airports between 2009 and 2019. The results suggest that residual airports have less unused capacity than compensatory airports. This can be explained by the control of signatory airlines over the residual airports' investment decisions and the lack of retained earnings under the residual agreement. We did not detect a significant difference in excess capacity between single-purpose and multipurpose governance forms. However, it is noteworthy that large hub airports exhibit higher capacity utilization compared to medium hub airports.

1. Introduction

Capacity utilization is vital to the profitability of airports. However, airports often face a lumpy capacity problem, holding excess capacity in the short run in consideration of the long-term capacity needs (Doganis, 1992). On the one hand, excess capacity can lead to economic inefficiencies, as resources are underutilized, and costs associated with maintaining unused infrastructure and services are incurred. On the other hand, underestimating capacity can result in congestion, delays, and increased costs for both airlines and airports due to operational disruptions and compromised service quality. Given these considerations, capacity expansion becomes a critical decision for airport authorities. Airport capacity utilization can be driven by demand uncertainty (Xiao et al., 2013), airline competition at the airport (Ciliberto & Williams, 2010; Zhang & Zhang, 2006), or the market structure of the industry (Esposito & Esposito, 1974; Wenders, 1971). However, the impact of airport business models on airport capacity investment decisions and utilization remains unexplored.

In recent years, airports and airlines have developed various vertical relationships to restore financial viability (Fu et al., 2011). The most common vertical relationship in the U.S. aviation industry is the use agreements, which can be compensatory, residual, or hybrid. Compensatory arrangements are also known as dual-till in other parts of the world, while the alternative term used for residual arrangements is single-till. The main distinction between the three types of agreements is in whether and how revenues airports make on the non-aeronautical side (this includes, for instance, revenues from terminal space rentals and parking on airport-operated parking facilities) are used to offset for aeronautical costs (the cost of running the infrastructure used by the airlines and airports' other customers for their operations). Under the residual agreement, profits an airport earns on the non-aeronautical side are used to offset the aeronautical costs, with the airlines covering the remainder of those costs. Compensatory agreements allow the airports to retain non-aeronautical profits with the airlines billed for the full extent of the aeronautical costs. Hybrid arrangements split non-aeronautical profits – the airport retains part of it, with the remaining profits used to offset some of the aeronautical costs.

As residual airports are unable to generate retained earnings, these airports predominantly finance their capital projects through the issuance of bonds. This heavy reliance on bonds ultimately results in a higher cost of capital in comparison to compensatory airports (Faulhaber et al., 2010). On the other hand, as a trade-off for a financial guarantee, signatory airlines[1] have control over airport investment decisions. This control is identified in the Majority in Interest (MII) clauses. According to MII, signatory airlines have the right to review and veto capital projects, which may significantly increase their rates and fees (Faulhaber et al., 2010; US Congress & Office of Technology Assessment, 1984). Overall, the nature of residual agreements can be associated with investment constraints. Unlike residual agreements, airports adopting the compensatory method do not have to use the surplus revenues to reduce airline rates. Thus, they may use retained earnings for capital development (US Congress & Office of Technology Assessment, 1984). Furthermore, under the compensatory method, MII is rarely seen. As the hybrid method is a combination of residual and compensatory methods, it includes attributes of both approaches.

U.S. airports are governed by city, county, state, and port/airport authorities (Kutlu & McCarthy, 2016). Based on their characteristics, they can be classified into two main categories: multipurpose (city, county, and state governance) and single-purpose (port/airport authority) (Reimer et al., 2009). One key characteristic is that the inherent specialization of single-purpose governments, exclusively dedicated to the management of airports, might yield distinct advantages. Notably, this specialization is anticipated to foster intensified expertise,

[1] Signatory airline refers to the one signing residual contract with the host airport.

expeditious decision-making, and higher flexibility in matters concerning workforce management and procurement of inputs (Mills et al., 2022). While recognizing the potential advantages linked to specialized single-purpose authorities, it is crucial to acknowledge the inherent risk tied to endowing these entities with increased autonomy in the absence of direct citizen accountability through elections. This autonomy may lead to higher "rent-seeking" tendencies within port/airport authorities, resulting in suboptimal decisions. Examples include the acquisition of inputs at costs exceeding opportunity costs or in quantities surpassing optimal thresholds(Reimer et al., 2009). Hence, the choice between reaping the benefits of specialization and navigating the potential drawbacks tied to heightened autonomy within airport authorities may become pivotal in determining the capacity utilization of these airports.

Considering the constraints and opportunities arising from airport business practices, we examine the impact of use agreements and governance forms on excess capacity. Besides, we incorporate hub size into the analysis to control for any size effect on capacity utilization. To the best of our knowledge, this research represents a pioneering effort in examining the relationship between airport business practices and unused capacity. Addressing this research gap, we aim to provide valuable insights into the factors influencing unused capacity within the airport industry. In addition, this study offers a comprehensive analysis of the advantages and disadvantages associated with different use agreements and governance forms, specifically in terms of their impact on capacity utilization.

The remainder of the paper is organized as follows. In the following section, we provide a brief discussion of the use agreements and governance forms. Section 3 includes a review of the relevant literature. Section 4 describes the methodology, while Section 5 introduces data.

The results are provided in Section 6. The last section concludes and offers a discussion of the policy implications of our results.

2. Use Agreements and Governance Forms

The airline deregulation in 1978 led to a structural change in the U.S. aviation industry. Albeit the deregulation substantially increased air traffic volume, it brought harsh competition to the market (Peterson, 2018). In this competitive environment, airlines seek partnership opportunities with airports to secure their slots in the long run and obtain reduced airport fees (Fu et al., 2011). On the other hand, Federal guidelines require the airports to be financially self-sustaining, even though they are owned by Federal, State, or local governments (Fu & Yang, 2017). Moreover, increasing traffic demand puts pressure on airports to increase their capacity. To address these issues, many airports also rely on vertical relationships with airlines. The most common vertical relationship in the U.S. is use agreements. Two primary use agreements are compensatory and residual. A new method, hybrid, has emerged in recent decades.

The residual method is designed to cover the financial risk of the host airport. Signatory airlines, in turn, may obtain reduced fees based on the year-end true-up process. Any surplus in total revenues is credited to the rates paid by the signatory airlines, while deficits are charged to the following year's fees (US Congress & Office of Technology Assessment, 1984). As a result, the financial guarantee provided by the signatory airlines make sure the host airport always breaks even. Therefore, the host airport does have less incentive to maximize non-aeronautical revenues and concerns about operating expenses (Faulhaber et al., 2010). Moreover, as any surplus in revenue is credited to signatory airlines, the host airports do not generate retained earnings (US Congress & Office of Technology Assessment, 1984). Thereby, they rely on bond finance for the majority of their capital projects, resulting in a higher cost of capital compared to compensatory airports (Faulhaber et al., 2010). While bonds mostly finance capital projects, the debt service which is used to pay the principal and interest of the bonds is covered by aeronautical and non-aeronautical revenues.

While any deficit resulting from excess debt is covered by signatory airlines; these airlines effectively control new capital projects which will be implemented by the airport. According to the Majority in Interest (MII) clause, signatory airlines have a right to review the new capital projects and approve or veto them (Faulhaber et al., 2010). For instance, in 2018, American Airlines opposed to O'Hare International Airport's $8.5 billion capacity expansion plan[2].

In contrast to the residual method, the compensatory method does not prioritize any airlines; thereby, the aeronautical fees are determined based on the usage of terminals and other airport facilities. As airports adopting the compensatory method do not share financial risk with the airlines; such airports may be more exposed to adverse air travel demand shocks. On the other hand, compensatory airports are able to generate retained earnings since they do not credit any surplus in revenue to an airline (US Congress & Office of Technology Assessment, 1984). Therefore, compensatory airports have stronger coverage for operating expenses and debt services. Besides, decisions on new capital projects fall entirely within the airports' purview (Faulhaber et al., 2010). As the name suggests, the hybrid method includes a mix of the

[2] https://www.chicagotribune.com/business/ct-biz-ohare-expansion-american-united-gate-competition-0304-story.html

elements of residual and compensatory approaches. For instance, airports may integrate the compensatory method into terminal operations, while using the residual method in airfield operations. Another practice of the hybrid method is revenue sharing. Although the compensatory method is adopted in both terminal and airfield operations, airports share non-aeronautical revenues with airlines to make aeronautical charges reasonable (Fu et al., 2011).

An international equivalent to “residual” rate-setting methodology is the approach known as “single-till”. Under this approach, non-aeronautical profit is used to offset aeronautical costs; with the airlines then billed for the remainder of those costs. “Dual-till” is the term equivalent to “compensatory” approach. Hybrid-till approaches are also becoming increasingly popular – for instance, Singapore Changi Airport uses half of its non-aeronautical profits to offset part of the aeronautical costs. While arrangements similar to the existence of signatory airlines and MII clauses are not common outside of the US market; airports in other countries often offer incentives, such as quantity discounts of aeronautical charges, discounted fees for transfer passengers, or reduced fees for new destinations. In the end, dominant carriers frequently end up receiving preferential treatment from the airports.

Albeit U.S. airports are public entities, the governance structures differ considerably across the airports. The most common governance forms are the city, county, state, and port/airport authority (Kutlu & McCarthy, 2016). Classifying airports based on governance attributes yields two categories: multipurpose and single-purpose. On the one hand, single-purpose governance offers distinct advantages, including heightened focus, increased autonomy from political influences, the ability to operate the airport as a business, innovative financing approaches, and the flexibility to navigate local procurement and hiring regulations

(Mills et al., 2022). On the other hand, multipurpose governments are often attuned to voter demands, potentially making them more responsive than authorities. Thus, these governments may actively pursue cost-effective strategies and offer levels of output in greater demand (Reimer et al., 2009).

3. Previous Studies

The nature of airport capacity investment – known as the lumpy capacity problem – often leads to excess capacity in the short run. Excess capacity may result from demand uncertainty, dominant carriers at the airport, or the industry's market structure. Xiao et al. (2013) pointed out that demand uncertainty alleviates excess capacity problems if the variation in demand is high, and the cost of capital is low. On the other hand, Ciliberto and Williams (2010) demonstrate that dominant carriers limiting the extent of airport expansion contributes to the reported hub premia in the US airline industry. Dresner et al. (2002) also found that the lack of capacity may be related to the barriers to entry of dominant airlines. Unlike these studies, Zhang and Zhang (2006) found that budget-constrained public airports are more prone to excess capacity when an airline has market power, as compared to subsidized public airports. On the other hand, monopolists use excess capacity as a barrier against new entrants (Wenders, 1971). Martín and Voltes-Dorta (2011) examined the capacity expansion decisions of multi-airport systems from all over the world in the years between 1991 and 2008. They found that adding more airports in the region decreases the economies of scale.

Another issue studied in the literature is the impact of the vertical relationship between airlines and airports on capacity decisions. Sarmento and Brandão (2013) is one of the pioneering studies to investigate the relationship between vertical relationships and airport capacity expansions. Of the three types of vertical relationships (vertical separation, vertical collusion, and profit sharing), the latter was found to provide the highest incentives to airports for investment. Xiao et al. (2016) also examined the impact of vertical relationships on airport capacity choices under demand uncertainty with a multi-stage game model. The authors found that vertical relationships lead to higher capacity and cost savings.

The relationship between use agreements and airports' efficiency has received a lot of attention in the literature. Gillen and Lall (1997) analyzed the effects of structural, environmental, and managerial factors on the productive efficiency of 21 U.S. airports in the years from 1989 to 1993 with a two-stage DEA model. One of the managerial factors is the use agreement methods. The authors found that the residual method leads to higher efficiency in airfield operations, while terminal operations are more efficient with a compensatory method. Vasigh and Hamzaee (1998) compared the financial performance of the airports in terms of use agreement methods. Their results suggest that compensatory methods contribute to airport profitability more than the residual method. Oum et al. (2004) focused on the relationship between use agreements and airport productivity. That study used data from 60 airports from all over the world in 1999. They found that total factor productivity is higher with the compensatory method (dual-till), while residual (single-till) approach leads to higher capital input productivity. More recently, Karanki and Lim (2020, 2021) assessed the impact of use agreements on the productive and cost efficiency of 59 U.S. airports. The authors found that the airports adopting the residual method were less productive and cost-efficient than compensatory and hybrid airports. The findings were tied to the argument: "airports under the residual agreement have less incentive to maximize non-aeronautical revenues and have less concern about operating expenses." They argued that the residual approach leads to moral hazard, as signatory airlines provide financial guarantees to the airports.

Apart from the effects of vertical relationships on airport efficiency, Oum et al. (2008) assessed the efficiency differences across governance forms with the data including 109 airports from all over the world in the years between 2001 and 2004. They found that municipal and State airports are more efficient than their peers operated by port authorities. Craig et al. (2012) focused on the U.S. airports in the period from 1979 to 1992. The major finding of the study is that airport authorities are more efficient than their counterparts. However, considering cost efficiency, the difference between municipal and airport authorities decreased by 5 percent due to overpayment, although airport authorities were still more cost-efficient. Zhao et al. (2014) examined 47 U.S. airports and found similar results that municipal and State-operated airports are less technically efficient than the ones governed by airport authorities. Kutlu and McCarthy (2016) assessed the cost-efficiency differences between four governance forms of U.S. large and medium hub airports, using the data from 1996 to 2008. They reported that local governance reduces cost efficiency whereas medium hub airports are more cost-efficient than large hub airports. Karanki and Lim (2020) also examined the impact of governance forms on airport technical efficiency. Their sample includes 59 U.S. large and medium hub airports from 2009 to 2016. They found that the airports governed by the States are less efficient than the airports governed by port/airport authority, whereas large-size airports are more efficient than medium airports.

This study addresses a notable research gap in the existing literature by specifically investigating the influence of use agreements and governance forms on capacity utilization in the airport industry. Previous studies have not explicitly examined this relationship, making our research a pioneering effort in linking business practices to the issue of excess capacity. The outcomes of our study not only fill an important research gap but also have practical implications for airport authorities and policymakers. The findings will enable informed decision-making regarding the selection of use agreements and the design of governance forms, with the ultimate goal of optimizing capacity utilization and reducing excess capacity in the airport industry.

4. Method

Most of the literature on airport capacity utilization has been based on the engineering definition of capacity (Evans & Schäfer, 2011; Gelhausen et al., 2013; Hu et al., 2022). While the engineering approach identifies the potential capacity as the maximum output per unit of time given short-run capital stock, the economic approach considers firm capacity choice based on marginal costs and input allocation (Nelson, 1989). The economic approach includes two different concepts: price information-based and physical information-based. The first concept introduced by Klein (1960) suggests that the optimal capacity occurs at the point where the long-run average cost curve and the short-run average cost curve are tangent. Following Klein (1960), Berndt and Morrison (1981) proposed that the minimum of the short-run average total cost curve represents the optimal capacity under the constant returns to scale assumption in the long run. Due to the lack of data on the cost of capital and input prices, the second economic capacity concept which is based on physical information is better suited for the airport industry. According to the physical information-based concept, Johansen (1968) defines capacity as: “the maximum amount that can be produced per unit of time with existing plant and equipment provided that the availability of variable factors of production is not restricted”. These three approaches are illustrated in Figure 1.

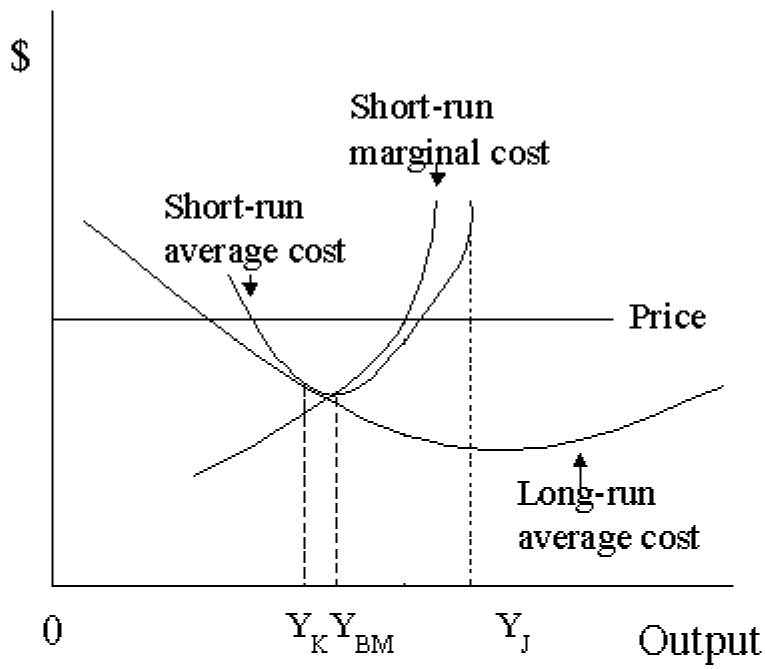

Figure 1-Comparison of Economic Capacity Measures. Source: Coelli et al. (2002)

To obtain the optimal capacity defined by Johansen (1968), we use a modified output-oriented data envelopment analysis (DEA) developed by Fare et al. (1989, 1994). The modified DEA model allows variable inputs to be unbounded.

Following Fare et al. (1989,1994), let j=1, …,J be decision-making units (DMUs), m=1,…,M denote outputs, and n=1,…, N inputs. The constrained optimization problem can then be formulated as follows:

$$TE_1 = \max_{\theta_1, z, \lambda} \theta_1 \quad (1)$$

s.t.

$$\theta_1 u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, n \in \alpha$$

$$\sum_{j=1}^{J} z_j x_{jn} = \lambda_{jn} x_{jn}, n \in \hat{\alpha}$$

$$z_j \geq 0$$

$$\lambda_{jn} \geq 0$$

where

u_{jm} is m^{th} output produced by j^{th} DMU.

x_{jn} is n^{th} input used by j^{th} DMU.

z_j is the intensity variable for j^{th} observation serving to form best practice technology by connecting the observed input and output points.

λ_{jn} $(\sum_{j=1}^{J} z_j x_{jn} / x_{jn})$ is variable input utilization rate, which is the ratio of optimal use of n^{th} input used by j^{th} DMU to the observed use.

θ is a scalar.

Model (1) achieves optimal capacity (θ_1) by utilizing variable inputs at the rate λ_{jn}. Accordingly, if $\lambda^* > 1$, the variable input is underutilized, namely, there is a shortage of variable inputs. Model (1) is built on the assumption of constant return to scale (CRS) technology (Charnes et al., 1978). Considering the inconsistency between output and input levels, we should also use variable returns to scale (VRS) technology. Therefore, we add the convexity constraint ($\sum_{j=1}^{J} z_j = 1$) to the model (Banker et al., 1984).

On the other hand, ignoring inefficiency in potential outputs would lead to a biased capacity utilization estimate (Fare et al., 1989, 1994). Therefore, the potential output is obtained from a standard output-oriented DEA model introduced by Farrell (1957). The model is specified as follows:

$$TE_2 = \max_{\theta_2, z, \lambda} \theta_2 \tag{2}$$

s.t.

$$\theta_2 u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}$$

$$z_j \geq 0$$

Model (2) also assumes CRS technology. To switch to VRS technology, the second constraint should be replaced as discussed above. As a result, the capacity utilization rate (CU^*) is the ratio of θ_2^* to θ_1^*. Capacity utilization rate less than one ($CU^* < 1$) refers to underutilized (excess) capacity held by an airport.

In the second stage, we conduct a truncated regression with a bootstrap procedure to measure the impact of environmental variables on capacity utilization, following Simar and Wilson (2007). The conventional censored regression and OLS methods lead to a bias resulting from correlation between environmental variables and error terms, and an unknown correlation among the DEA scores. To eliminate this bias, Simar and Wilson (2007) suggested a two-sided truncated regression with a bootstrap procedure. Our model is formulated as follows:

$$CU_{it}^{*} = z_{it}\beta + \varepsilon_i \tag{3}$$

where z_{it} is a vector of environmental variables and β is the vector of the coefficient estimates. The environmental variables are use agreements, governance forms, and airport size. Specifically:

$$z_{it}\beta = \beta_0 + \beta_1 Compensatory_i + \beta_2 Hybrid_i + \beta_3 Multipurpose_i + \beta_4 Large_i \tag{4}$$

As our overarching goal is assessing the impact of use agreements on capacity utilization, use agreements are induced into the model as dummy variables. *Residual* is chosen as the omitted group, while *Compensatory* and *Hybrid* indicator variables are added to the model. Secondly, we added governance forms to the model as binary variables to examine their impact on capacity utilization. Thus, *Multipurpose* was added to the model. Finally, the size effect is controlled with *Large*, which is a simple indicator for airports classified by the FAA as large hubs.

5. Data

Our data includes 30 large hub and 29 medium hub airports in the years from 2009 to 2019. The list of airports can be found in Appendix A.1. To obtain the capacity utilizations, we incorporate three outputs, two variable inputs, and two fixed inputs into our model. The data sources are reported in Table 1. The outputs are the number of aircraft movements (ATM), the number of passengers (PAX), and cargo weight in pounds (CAR). ATM comes from the FAA Operations Network Data System, whereas data for PAX and CAR variables come from the Certification Activity Tracking System (CATS), also by the FAA.

The fixed inputs are the number of gates (GATE) and the effective number of standard runways (ENSR). As the output of airports depends on the dimensions of runways, the number of runways alone is not a reliable measure of capacity. Thus, following McCarthy (2014), we use ENSR as a fixed input. After obtaining the dimension of runways from the FAA Aeronautical Information Service, we calculated the ENSR as $\sum_r \frac{(Length_{rit})(Width_{rit})}{1{,}500{,}000}$. GATE was obtained from airports' web pages. Two variable inputs are the number of employees (EMP) which is full time equivalent employees at the end of the fiscal year, and operating expenses less salaries and benefits (OPEX). Both come from CATS. Besides, we focus on three environmental variables: use agreements, governance forms, and airport size. We initially obtained the information on use agreements up to 2016 from LeighFisher (2016). Subsequently, we updated the agreements with expiration dates falling between 2017 and 2019 based on the data from DWU Consulting (2022). Governance forms come from National Academies of Sciences, Engineering (2009). Table 1 depicts the data sources. We obtained the information on airport size from FAA.

Table 1-Data Sources

Variable	Source
Outputs	
ATM	Operations Network Data System of FAA (https://aspm.faa.gov/)
PAX	CATS (https://cats.airports.faa.gov/Reports/reports.cfm)
CAR	CATS (https://cats.airports.faa.gov/Reports/reports.cfm)
Variable Inputs	
EMP	CATS (https://cats.airports.faa.gov/Reports/reports.cfm)
OPEX	CATS (https://cats.airports.faa.gov/Reports/reports.cfm)
Fixed Inputs	
GATE	Airport Webpages
ENSR	FAA Aeronautical Information Service (https://www.faa.gov/air_traffic/flight_info/aeronav/aero_data/Airport_Data/)
Environmental variables	
Large Hub (*Large*)	FAA (https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/)
Use agreements	LeighFisher (2016) and DWU Consulting LLC (https://dwuconsulting.com/)
Governance Forms	National Academies of Sciences, Engineering (2009)

Table 2 shows the distribution of our sample airports based on use agreement types and governance forms. The most common governance form is multipurpose. As far as the user agreements go, while the hybrid method is the most common use agreement in our dataset, the distribution of airports by the use agreement types is close to uniform. Interestingly, few single-purpose governed airports adopt the residual method, which is the most popular one among airports governed by multipurpose authorities.

Table 2-Summary of Airports Classification

	Multipurpose	**Single Purpose**	**Total**

Compensatory	9	8	17
Hybrid	11	14	25
Residual	14	3	17
Total	34	25	59

In Table 3, we summarize our data by year. While the average number of aircraft movements decreased from 288.8K in 2009 to 285.6K in 2019; the mean number of passengers increased from 10,417.7K to 13,914.1K over the same period. These changes are consistent with the increase in the average aircraft size and/or passenger load factors after the 2008 financial crisis (DOT-Office of Inspector General, 2012). Besides, cargo weight substantially increased in parallel to the number of passengers. On the other hand, operating expenses less salaries and benefits, which is one of the variable inputs we use, increased by 51.6 percent. The other variable input, the number of employees, on average, increased from 557.9 in 2009 to 620.2 in 2019.

Table 3- Summary Statistics of Variables by Year

Year	# of Obs.	Variable	Mean	Std Dev	Minimum	Maximum
2009	59	ATM($x10^3$)	288.8	184.7	83.5	970.3
		PAS($x10^3$)	10417.7	8916.2	1730.9	44809.0
		CAR($x10^3$)	2010822.5	3282226.3	2170.5	15524360.0
		OPEX	154759.6	132381.7	19042.9	670230.6
		EMP	557.9	508.5	105.0	3252.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.0	0.6	11.8
2010	59	ATM($x10^3$)	288.7	190.2	83.6	950.1
		PAS($x10^3$)	10540.4	9109.0	1694.1	45375.3
		CAR($x10^3$)	2140745.7	3642676.3	2145.2	19463543.8
		OPEX	159243.4	133930.9	19279.6	664652.1
		EMP	547.4	495.4	105.0	3130.0
		GATE	70.9	48.1	14.0	193.0

		ENSR	3.4	2.0	0.6	11.8
2011	59	ATM(x10^3)	288.8	190.5	83.0	924.0
		PAS(x10^3)	10806.4	9349.6	1748.4	46191.7
		CAR(x10^3)	2127831.1	3559718.1	2192.1	17774071.2
		OPEX	168694.9	146160.8	23494.7	743081.5
		EMP	552.0	493.8	105.0	3130.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.0	0.6	11.8
2012	59	ATM(x10^3)	284.4	191.7	79.2	930.1
		PAS(x10^3)	10957.5	9582.7	1824.3	47147.3
		CAR(x10^3)	2119231.9	3555563.7	2282.7	17212229.0
		OPEX	174528.6	151784.8	17970.7	751320.6
		EMP	554.8	510.8	108.0	3226.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.0	0.6	11.8
2013	59	ATM(x10^3)	282.8	191.7	79.2	911.1
		PAS(x10^3)	11081.9	9726.1	1845.1	47526.2
		CAR(x10^3)	2182157.3	3600140.8	2321.9	17485003.0
		OPEX	181930.6	158646.5	22049.9	758745.5
		EMP	553.2	504.5	115.0	3174.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.8
2014	59	ATM(x10^3)	280.2	189.7	77.1	881.9
		PAS(x10^3)	11356.7	9999.8	1847.3	47318.8
		CAR(x10^3)	2220501.5	3596732.6	2241.6	17309490.0
		OPEX	190205.7	165773.6	21720.9	782694.7
		EMP	564.6	516.7	117.0	3235.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.9
2015	59	ATM(x10^3)	282.1	190.4	79.3	882.5
		PAS(x10^3)	11882.3	10487.1	1886.2	49056.3
		CAR(x10^3)	2364283.9	3811035.5	2251.6	17269809.0
		OPEX	190728.7	162594.3	23419.6	752724.9
		EMP	569.7	509.4	117.0	3167.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.9
2016	59	ATM(x10^3)	287.2	192.4	79.1	898.4
		PAS(x10^3)	12442.7	10977.2	1867.3	51807.4
		CAR(x10^3)	2453315.3	3858641.9	2235.1	17698807.6
		OPEX	202352.8	172606.7	23879.8	747921.7
		EMP	579.5	520.7	120.0	3239.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.9

2017	59	ATM(x10^3)	292.1	187.9	82.6	879.5
		PAS(x10^3)	12809.4	11218.8	1465.4	52098.0
		CAR(x10^3)	2548731.7	3899969.7	3766.3	17418635.5
		OPEX	208863.9	180299.1	23984.6	756688.3
		EMP	598.0	558.1	32.0	3500.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.9
2018	59	ATM(x10^3)	299.2	191.7	82.4	903.7
		PAS(x10^3)	13436.8	11571.6	2072.1	52562.2
		CAR(x10^3)	2637739.5	3932270.2	3898.3	18413943.9
		OPEX	220301.5	190340.6	24937.5	799958.5
		EMP	607.5	567.8	35.0	3589.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.9
2019	59	ATM(x10^3)	285.6	200.7	72.8	915.4
		PAS(x10^3)	13914.1	11919.5	2204.1	54531.9
		CAR(x10^3)	2732307.7	4005109.0	3913.5	18355942.1
		OPEX	234546	209666.3	27131.9	837926.2
		EMP	620.2	578.2	45.0	3597.0
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.9
Overall	59	ATM(x10^3)	287.3	191.1	80.2	913.4
		PAS(x10^3)	11786.0	10259.8	1835.0	48947.6
		CAR(x10^3)	2321606.2	3704007.6	2674.4	17629621.4
		OPEX	189650.5	164016.8	22446.6	751449.5
		EMP	573.2	524.0	91.3	3294.5
		GATE	70.9	48.1	14.0	193.0
		ENSR	3.4	2.1	0.6	11.8

Table 4 represents the descriptive statistics of inputs and outputs in 2019 based on use agreement types. The highest outputs are observed at the airports adopting the compensatory method. Residual airports follow them. Looking at the variable inputs, compensatory airports have the highest number of employees and the highest operating expenses. The residual airports hold the second rank in this category. However, the average values of the fixed input variables are the highest for residual airports, followed by compensatory airports.

Table 4-Summary Statistics by Use Agreement Methods

Use Agreement	# of Obs.	Variable	Mean	Std Dev	Minimum	Maximum
Compensatory	17	ATM($x10^3$)	306.8	207.5	78.1	717.8
		PAS($x10^6$)	15.9	13.1	2.21	44.2
		CAR($x10^6$)	3188.8	4434.3	263.5	18355.9
		OPEX($x10^6$)	296	268	27.1	836
		EMP	715.3	886.9	125	3597
		GATE	67.8	43.7	20.0	146.0
		ENSR	3.6	2.9	0.6	11.8
Hybrid	25	ATM($x10^3$)	272.7	197.7	72.7	900.5
		PAS($x10^6$)	12.9	11.9	2.52	54.5
		CAR($x10^6$)	2179.3	3171.3	3.9	13799.8
		OPEX($x10^6$)	187	145	41.3	593
		EMP	521.8	311.2	147	1305
		GATE	66.9	47.9	14	192
		ENSR	3.1	1.7	1.2	8.1
Residual	17	ATM($x10^3$)	283.2	208.5	89.7	915.4
		PAS($x10^6$)	13.3	11.2	2.63	42.2
		CAR($x10^6$)	3089.1	4750.1	42.7	18306.6
		OPEX($x10^6$)	243	220	55.4	838
		EMP	669.7	502.7	45	1582
		GATE	79.8	53.9	26	193
		ENSR	3.7	1.4	1.7	6.4

6. Results

As noted above, the capacity utilization rates, optimal capacity, variable input utilization rates, and technical efficiency of airports were estimated by two output-oriented DEA models. We ran these models for each year, considering only peer comparison. Since we do not have enough information on technology, we repeated the models under both CRS and VRS technology assumptions. The summary statistics of the CRS and VRS estimates are reported in Tables 5 and 6, respectively.

Table 5-DEA Estimates with CRS Technology

		$\boldsymbol{\theta_1^*}$	$\boldsymbol{\theta_2^*}$	$\boldsymbol{CU^*}$	$\boldsymbol{\lambda_{Opex}^*}$	$\boldsymbol{\lambda_{Emp}^*}$
2009	Mean	1.57	1.40	0.91	1.59	1.38
	SD	0.44	0.36	0.10	1.05	0.90
	Min	1.00	1.00	0.66	0.40	0.20
	Max	3.41	2.99	1.00	5.69	4.95
2010	Mean	1.58	1.41	0.90	1.59	1.46
	SD	0.46	0.39	0.10	0.93	0.93
	Min	1.00	1.00	0.65	0.45	0.21
	Max	3.45	3.07	1.00	5.38	5.09
2011	Mean	1.56	1.38	0.89	1.71	1.55
	SD	0.45	0.37	0.10	1.03	0.88
	Min	1.00	1.00	0.65	0.43	0.29
	Max	3.30	2.85	1.00	5.27	5.14
2012	Mean	1.61	1.40	0.89	1.74	1.59
	SD	0.49	0.39	0.11	1.14	0.89
	Min	1.00	1.00	0.58	0.43	0.30
	Max	3.55	3.01	1.00	6.74	5.03
2013	Mean	1.65	1.42	0.88	1.87	1.52
	SD	0.52	0.39	0.11	1.20	0.81
	Min	1.00	1.00	0.55	0.48	0.30
	Max	3.64	2.94	1.00	6.25	4.47
2014	Mean	1.66	1.41	0.87	1.84	1.56
	SD	0.54	0.39	0.12	1.16	0.79
	Min	1.00	1.00	0.55	0.48	0.31
	Max	3.72	3.00	1.00	6.03	4.48
2015	Mean	1.66	1.39	0.86	1.90	1.55
	SD	0.54	0.38	0.12	1.18	0.78
	Min	1.00	1.00	0.51	0.53	0.30
	Max	3.55	2.87	1.00	6.28	4.45
2016	Mean	1.64	1.35	0.85	1.86	1.58
	SD	0.53	0.36	0.13	1.15	0.76
	Min	1.00	1.00	0.47	0.54	0.71
	Max	3.56	2.86	1.00	6.01	4.51

2017	Mean	1.74	1.36	0.82	1.72	1.84
	SD	0.61	0.35	0.17	0.80	1.33
	Min	1.00	1.00	0.38	0.61	0.54
	Max	3.61	2.68	1.00	4.12	7.42
2018	Mean	1.73	1.33	0.81	1.77	1.95
	SD	0.63	0.35	0.16	0.79	1.44
	Min	1.00	1.00	0.39	0.66	0.52
	Max	3.67	2.78	1.00	4.15	9.04
2019	Mean	1.63	1.29	0.83	2.01	1.88
	SD	0.57	0.31	0.14	1.09	1.31
	Min	1.00	1.00	0.46	0.67	0.54
	Max	3.61	2.67	1.00	6.17	7.78

Table 6-DEA Estimates with VRS Technology

		$\boldsymbol{\theta_1^*}$	$\boldsymbol{\theta_2^*}$	$\boldsymbol{CU^*}$	$\boldsymbol{\lambda_{Opex}^*}$	$\boldsymbol{\lambda_{Emp}^*}$
2009	Mean	1.53	1.33	0.89	1.35	1.29
	SD	0.44	0.37	0.14	0.69	0.79
	Min	1.00	1.00	0.41	0.40	0.20
	Max	3.41	2.99	1.00	4.05	4.33
2010	Mean	1.53	1.33	0.89	1.54	1.39
	SD	0.46	0.39	0.13	0.82	0.81
	Min	1.00	1.00	0.43	0.45	0.21
	Max	3.45	3.07	1.00	4.44	4.17
2011	Mean	1.51	1.32	0.89	1.63	1.49
	SD	0.45	0.37	0.12	0.88	0.78
	Min	1.00	1.00	0.45	0.43	0.29
	Max	3.30	2.85	1.00	4.34	4.33
2012	Mean	1.54	1.33	0.88	1.48	1.54
	SD	0.48	0.38	0.13	0.78	0.81
	Min	1.00	1.00	0.48	0.43	0.30
	Max	3.55	3.01	1.00	4.22	4.22
2013	Mean	1.58	1.34	0.87	1.77	1.48
	SD	0.51	0.39	0.14	1.02	0.75
	Min	1.00	1.00	0.46	0.48	0.30

	Max	3.64	2.94	1.00	5.79	3.90
2014	Mean	1.59	1.33	0.86	1.73	1.50
	SD	0.54	0.38	0.14	0.99	0.72
	Min	1.00	1.00	0.47	0.48	0.31
	Max	3.72	3.00	1.00	5.19	3.88
2015	Mean	1.59	1.32	0.86	1.79	1.50
	SD	0.53	0.37	0.14	0.98	0.72
	Min	1.00	1.00	0.50	0.53	0.30
	Max	3.55	2.87	1.00	4.78	3.94
2016	Mean	1.58	1.28	0.84	1.66	1.40
	SD	0.52	0.36	0.16	0.86	0.57
	Min	1.00	1.00	0.41	0.54	0.49
	Max	3.56	2.86	1.00	4.78	2.82
2017	Mean	1.66	1.29	0.82	1.68	1.78
	SD	0.59	0.35	0.18	0.77	1.34
	Min	1.00	1.00	0.38	0.61	0.55
	Max	3.61	2.68	1.00	4.12	8.41
2018	Mean	1.65	1.26	0.81	1.68	1.77
	SD	0.60	0.34	0.17	0.75	1.28
	Min	1.00	1.00	0.37	0.66	0.53
	Max	3.67	2.78	1.00	3.97	8.24
2019	Mean	1.56	1.22	0.82	1.85	1.79
	SD	0.53	0.30	0.16	0.92	1.24
	Min	1.00	1.00	0.38	0.67	0.54
	Max	3.61	2.65	1.00	4.49	7.24

Looking at Tables 5 and 6, the optimal capacities with CRS technology are slightly higher than those with VRS technology. However, both sets of estimates suggest that airports could have higher optimal capacity if they fully utilized variable inputs. For instance, with CRS technology, if the variable inputs (the number of employees and operating expenses) were maximized in 2019, they could achieve 63 percent more capacity. Besides, we found a significant shortage in variable inputs as $\boldsymbol{\lambda}^{*}_{\boldsymbol{Opex}} > 1$ and $\boldsymbol{\lambda}^{*}_{\boldsymbol{Emp}} > 1$. Further, technical efficiency scores differ between the two technologies. The technical efficiency of airports under the CRS technology assumption is higher than those under VRS technology. Nevertheless, we detected an improvement in the technical efficiency over the years, i.e., it progressed from 1.40 in 2009 to 1.29 in 2019 based on CRS estimates. The difference in capacity utilization rates between the two technologies is insignificant. Both CRS and VRS results demonstrate a slight trend toward increase in excess capacity. Looking at Table 5, for instance, CU decreased from 91 percent in 2009 to 83 percent in 2019.

In the second stage, following Simar and Wilson (2007), we conducted a two-sided truncated regression with 1000 bootstrap replications. CU obtained from the first stage was regressed on the environmental variables. The estimates with CRS and VRS technologies are reported in Table 7.

Table 7-Second Stage Estimates-Truncated Regression with Bootstrap Procedure

	CRS		**VRS**	
	Estimate	Bootstrap S.E.	Estimate	Bootstrap S.E.
Compensatory	-0.0712***	0.0218	-0.0848***	0.0290
Hybrid	-0.0085	0.2052	-0.0323	0.0272
Multipurpose	-0.0198	0.0170	0.0164	0.0226
Large	0.1898***	0.0224	0.3066***	0.0344
Intercept	0.8381***	0.0203	0.8099***	0.0278
Wald chi2(4)	80.39***		82.91***	
Number of Obs.	493		477	

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Wald Chi-Squared statistics confirm the significance of our model. Three results are consistent across the two specifications. First, airports adopting the compensatory method have lower capacity utilization rates than their peers adopting the residual method. Second, there is no difference between multipurpose and single-purpose airports. Third, large hub airports operate closer to their capacity as compared to medium hubs.

As the lower capacity utilization rate signifies excess capacity, compensatory airports hold higher excess capacity than residual airports. This can be explained by (i) the control of signatory airlines over capacity expansion decisions of residual airports, and (ii) the higher cost of capital that residual airports face due to the lack of retained earnings. On the other hand, we could not detect any significant difference in capacity utilization rates between hybrid and residual methods. This may indicate the similarities in business practices between hybrid and residual methods are more than those between compensatory and residual airports. Even though hybrid approach implies the airports' ability to retain some of their earnings; our results demonstrate that such retention does not appear to translate into capacity expansion. In addition, when examining both CRS and VRS estimates, there is no notable distinction between single-purpose and multipurpose airports. Consequently, it can be inferred that the impact of specialization offsets the impact on autonomy for single-purpose airports. Finally, large hub airports have higher capacity utilization rates than medium airports based on both CRS and VRS estimates. This result can in part by driven by the fact that large hub airports are more likely to operate as hubs in the airlines' hub-and-spoke networks[3]. Moreover, once an airline's hub

[3] We should note that the FAA classification of airports into large, medium, and small hubs is based on the passenger volumes rather than the airports' roles in the airlines' networks.

reaches its capacity, the hub operator will have limited opportunities to increase its traffic to the spoke airports in its networks, including medium hub airports in our data. Medium hubs are also more likely to be affected by the lumpy capacity problem.

7. Conclusion

Lumpy capacity is a chronic problem as the airports hold excess capacity in the short run, considering long-run needs. Excess capacity can be explained by economic factors such as demand uncertainty, the market concentration at airports, and market structure in the airport industry. However, business practices can also influence excess capacity. This study considers the relationship between airport capacity utilization on one hand, and use agreements, airport governance forms, and hub size on the other.

Due to the nature of the residual agreements, the host airports cannot generate retained earnings. Thus, they need to finance their capital investment with bonds, which results in a higher cost of capital. Moreover, the principal and interest payments in the debt service center are covered by operational revenues. As the operational revenues directly affect the fees paid by signatory airlines, the signatory airlines have the right to review, approve, or veto the new capital projects according to the Majority in Interest (MII) clauses. In contrast to the residual method, under the compensatory approach, there is no constraint on airports' investment decisions as the host airports bear the financial risk alone. Besides, airports have retained earnings since they do not have to use any surplus to reduce the signatory airlines' fees. Therefore, the cost of capital for compensatory airports is lower as compared to residual airports. The hybrid method includes the characteristics of both methods.

On the other hand, in the United States, we observe different airport governance structures, even though all commercial service airports in the country are publicly owned entities. Airports under the direct management of local, regional, or state governments are categorized under multipurpose governance, whereas those governed by port/airport authorities are classified as single-purpose governance. To examine the impact of these factors on capacity utilization, we employ a two-stage semiparametric method. In the first step, we conducted two DEA models which are a modified DEA based on Johansen (1968)'s capacity decision and a standard DEA. The second stage incorporates a two-sided truncated regression with a bootstrap process.

The results from the first stage analysis suggest that airports could achieve higher capacity by utilizing the variable inputs. For instance, if they hired more employees and spent more on operations, they could, on average, increase their capacity by 63 percent in 2019. Besides, the average technical efficiency increased over the years. As capacity utilization rates declined, excess capacity, on average, increased during the sample period. In the second stage, we found that airports adopting the compensatory method have lower capacity utilization rates than residual airports. Thus, the control of the signatory airline over residual airports' investment decisions and the lack of retained earnings result in less unused capacity. We did not detect any difference in capacity utilization rates between hybrid and residual methods. This implies that the similarities between hybrid and residual methods are more than those between hybrid and compensatory approaches. In addition, there is no significant difference between single-purpose and multipurpose airports in terms of unused capacity. This implies that the influence of specialization counteracts the effect on autonomy for single-purpose airports. Finally, large hub airports have higher capacity utilization rates than medium hub airports. The key result as far as the relationship between airport governance forms and capacity utilization is concerned is that the establishment of independent port/airport authorities does not increase the capacity utilization rates.

The nuanced dynamics of use agreements within the aviation sector present both advantages and challenges for host airports. One notable trade-off is evident in the relationship between financial guarantees and capital investments. As part of this trade-off, the approval process by signatory airlines under the residual agreement becomes pivotal in shaping the capital landscape of airports. This intricate interplay prompts a critical examination of the need for clear and comprehensive guidelines governing such negotiations and their subsequent execution. Recognizing the need for a delicate equilibrium, policymakers are urged to contemplate the establishment of standardized frameworks. These frameworks should navigate the delicate balance between providing financial security to airlines, a key component of use agreements, and granting airports the flexibility required for strategic capital investments. Striking this equilibrium is crucial for fostering an environment where both parties can thrive symbiotically while contributing to the overall sustainability of the aviation industry. Moreover, our study reveals a compelling correlation between the use agreements and capacity utilization at airports. This nexus draws attention to the imperative for policies explicitly designed to address the intricate challenges of capacity management. Policymakers could explore a spectrum of strategies, from incentivizing efficient capacity utilization to implementing regulations that ensure use agreements align with broader objectives of optimizing resources. In essence, the multifaceted nature of use agreements necessitates a holistic policy approach that goes beyond mere regulation. It calls for the establishment of frameworks that not only safeguard the financial interests of airlines and airports but also encourage practices that contribute to the efficient use of airport capacity. As policymakers chart the course for the aviation industry, they play a pivotal role in shaping an environment where use agreements become instruments of sustainable growth and resource optimization.

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Appendix

A.1. Airport classification

ID	Name	Governance Forms	Hub Size	Agreement Typet
ABQ	Albuquerque International Sunport	City	Medium	Compensatory
ANC	Ted Stevens Anchorage International Airport	State	Medium	Residual
ATL	Hartsfield–Jackson Atlanta International Airport	City	Large	Hybrid
AUS	Austin-Bergstrom International Airport	City	Medium	Compensatory
BDL	Bradley International Airport	Port/Airport Authority	Medium	Compensatory
BNA	Nashville International Airport	Port/Airport Authority	Medium	Hybrid
BOS	Gen. Edward Lawrence Logan International Airport	Port/Airport Authority	Large	Compensatory
BUF	Buffalo Niagara International Airport	Port/Airport Authority	Medium	Hybrid
BWI	Baltimore/Washington International Thurgood Marshall Airport	State	Large	Compensatory
CLE	Cleveland-Hopkins International Airport	City	Medium	Residual
CLT	Charlotte/Douglas International Airport	City	Large	Hybrid
CMH	John Glenn Columbus International Airport	Port/Airport Authority	Medium	Hybrid
CVG	Cincinnati/Northern Kentucky International Airport	Port/Airport Authority	Medium	Hybrid
DCA	Ronald Reagan Washington National Airport	Port/Airport Authority	Large	Hybrid
DEN	Denver International Airport	City	Large	Hybrid
DFW	Dallas/Fort Worth International Airport	City	Large	Compensatory
DTW	Detroit Metropolitan Wayne County Airport	County	Large	Residual
EWR	Newark Liberty International Airport	Port/Airport Authority	Large	Compensatory

FLL	Fort Lauderdale–Hollywood International Airport	County	Large	Residual
HNL	Daniel K. Inouye International Airport	State	Large	Hybrid
HOU	William P. Hobby Airport	City	Medium	Hybrid
IAD	Washington Dulles International Airport	Port/Airport Authority	Large	Hybrid
IAH	George Bush Intercontinental Airport	City	Large	Hybrid
IND	Indianapolis International Airport	Port/Airport Authority	Medium	Residual
JAX	Jacksonville International Airport	Port/Airport Authority	Medium	Hybrid
JFK	John F. Kennedy International Airport	Port/Airport Authority	Large	Compensatory
LAS	McCarran International Airport	County	Large	Residual
LAX	Los Angeles International Airport	City	Large	Compensatory
LGA	LaGuardia Airport (and Marine Air Terminal)	Port/Airport Authority	Large	Compensatory
MCI	Kansas City International Airport	City	Medium	Residual
MCO	Orlando International Airport	Port/Airport Authority	Large	Hybrid
MDW	Chicago Midway International Airport	City	Large	Residual
MIA	Miami International Airport	County	Large	Residual
MKE	General Mitchell International Airport	County	Medium	Residual
MSP	Minneapolis–St. Paul International Airport	Port/Airport Authority	Large	Hybrid
MSY	Louis Armstrong New Orleans International Airport	City	Medium	Residual
OAK	Oakland International Airport	Port/Airport Authority	Medium	Hybrid
OGG	Kahului Airport	State	Medium	Hybrid
OKC	Will Rogers World Airport	City	Medium	Compensatory
OMA	Eppley Airfield	Port/Airport Authority	Medium	Compensatory
ONT	Ontario International Airport	Port/Airport Authority	Medium	Residual
ORD	Chicago O'Hare International Airport	City	Large	Residual
PBI	Palm Beach International Airport	County	Medium	Hybrid
PDX	Portland International Airport	Port/Airport Authority	Large	Hybrid

PHL	Philadelphia International Airport	City	Large	Residual
PHX	Phoenix Sky Harbor International Airport	City	Large	Compensatory
PIT	Pittsburgh International Airport	Port/Airport Authority	Medium	Residual
RDU	Raleigh-Durham International Airport	Port/Airport Authority	Medium	Compensatory
RSW	Southwest Florida International Airport	Port/Airport Authority	Medium	Hybrid
SAN	San Diego International Airport	Port/Airport Authority	Large	Hybrid
SAT	San Antonio International Airport	City	Medium	Hybrid
SEA	Seattle–Tacoma International Airport	Port/Airport Authority	Large	Compensatory
SFO	San Francisco International Airport	City	Large	Residual
SJC	Norman Y. Mineta San José International Airport	City	Medium	Hybrid
SLC	Salt Lake City International Airport	City	Large	Hybrid
SMF	Sacramento International Airport	County	Medium	Compensatory
SNA	John Wayne Airport	County	Medium	Compensatory
STL	St. Louis Lambert International Airport	City	Medium	Residual
TPA	Tampa International Airport	Port/Airport Authority	Large	Hybrid

ƚ During the sample period, several airports switched their use agreements. ABQ: from residual to compensatory in July 2016; BNA: from residual to hybrid in July 2015; BUF: from compensatory to hybrid in April 2019; IAH: compensatory to hybrid in January 2018; JAX: from residual to hybrid in July 2017; MCI: from compensatory to residual in April 2017; SAN: from compensatory to hybrid in July 2018.