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Valuation of flexibility and investment timing in airport infrastructure projects: Cases in airport expansions and alternate design alternate bid bidding

Ilker Karaca
Iowa State University

Valuation of flexibility and investment timing in airport infrastructure projects: Cases in airport expansions and alternate design alternate bid bidding

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Ilker Karaca

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Major: Civil Engineering (Construction Engineering and Management)

Program of Study Committee:
Douglas D. Gransberg, Major Professor
Peter T. Savolainen
Hyung Seok "David" Jeong
Kristen S. Cetin
Travis R. A. Sapp

The student author and the program of study committee are solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

This work is dedicated to my grandparents, Fatma and Nazmi Kislak, Fatma and Mustafa Karaca, and to my family.

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ABSTRACT

Many large infrastructure projects are subject to considerable uncertainty over their revenue streams which makes their valuations particularly challenging. When project scalability can be altered as new information is revealed over the course of a project's lifecycle, the presence of uncertainty can, in fact, provide option values that are ignored with static Net Present Value (NPV) analyses. To achieve these benefits, however, a better understanding of volatility is of the essence. This dissertation seeks to demonstrate how a better understanding of the business risks could facilitate the valuation of flexibility options in investment timing and engineering design. It also details how the need to acquire such options may vary across different contexts (i.e., among airports of different sizes and different pavement types). The dissertation first demonstrates the mechanics of this complex concept by applying it to the simpler problem of volatility in airport pavement materials using the alternate design/alternative bid (ADAB) process common in highway construction. The research then proceeds to fully develop the approach for application to airport expansion projects. The results contribute to a better understanding of volatility of airport activity in US airports by relating option values to airports' concentration risk in their connecting traffic volumes. Finally, the presence of any stationarity behavior in airport capacity utilization levels is examined to test the existence of a constant mean and variance in the long run, which may assist the forecasting efforts associated with airport expansion projects. The major contribution of the dissertation is the explicit formulation of an equation for airport activity levels, which relates changes (hereafter termed "jumps") in passenger enplanements to the valuation of airport expansions.

CHAPTER 1. INTRODUCTION

With constantly evolving future infrastructure needs, air traffic and passenger volume, and shifting of airline hubs, airport capital investment decisions involve unique challenges and necessitate an increasingly dynamic approach to the availability of new information. In addition, as the overall travel and freight demand grows, the expansion capacity of smaller airports to alleviate growing pressure on major gateway airports is becoming increasingly important. In fact, airport expansion projects remain as the main method of adding capacity to the air transportation system. Yet such expansion options may come at a significant cost. When future expansion plans are integrated into airport planning, they impose considerable opportunity costs to accommodate future demand long before such demand arises. Similarly, failure to timely exercise expansion capabilities often leads to overexpansion or suboptimal capacity expansion when faced with increased future demand.

Airport infrastructure projects, such as terminal expansions, require significant sums of investment, and a static net present value (NPV) analysis, based on a simple discounted cash flow analysis may fail to capture the true value of airport expansion projects. Instead, a sequential investment approach, through a real options valuation methodology, could help better prioritize investment projects, and provide the flexibility needed for future expansion capabilities (Shockley 2007). In lieu of “now-or-never” analyses, real options models allow the decision maker to make an initial investment—and pay an option premium—in return for having the flexibility to scale up or defer investment until additional information on the project’s viability becomes available. The research places a particular emphasis on exploring the source of uncertainty and modeling the business risk in a way value of flexibility options can be captured.

Contributing to the growing literature (de Neufville 2008, de Neufville and Scholtes 2011; Hengels 2005) that recognizes the value of flexibility in infrastructure projects, this study takes a dedicated approach to examine how airport planning and investment decisions can benefit from new insights in this field.

More generally, the goal of this study is to answer two research questions:

1. How can the flexibility options present in major transportation investments be identified, and be explicitly modeled to interact with the underlying uncertainties for their services and the capacity utilization levels of their facilities;
2. Given the many complexities involved in modeling service demand and optimal capacity (Spitz and Golaszewski 2007; Kincaid et al. 2012; Bhadra and Schaufele 2007), can managers learn from studying actual demand data to make a minimal set of assumptions when forecasting the efficient use of capacity created by expansion projects?

This dissertation is organized as follows (Figure 1-1 provides an overview of the three papers included here). The next section provides a summary of the main findings and their significance to the field. While the remainder of the chapter introduces a few key concepts that are mentioned throughout the text, the emphasis is given to perpetual options, which is believed to provide a motiving starting point on the main trade-offs involving expansion options and their exercise. Whereas Chapter 2 (Figure 1-2) and Chapter 3 (Figure 1-3) relate to the set of challenges invoked by the first research question, Chapter 4 (Figure 1-4) is dedicated to studying the stationarity in airport capacity use levels, which concerns the second research question. A list of the main conclusions of each chapter is provided in Chapter 5.

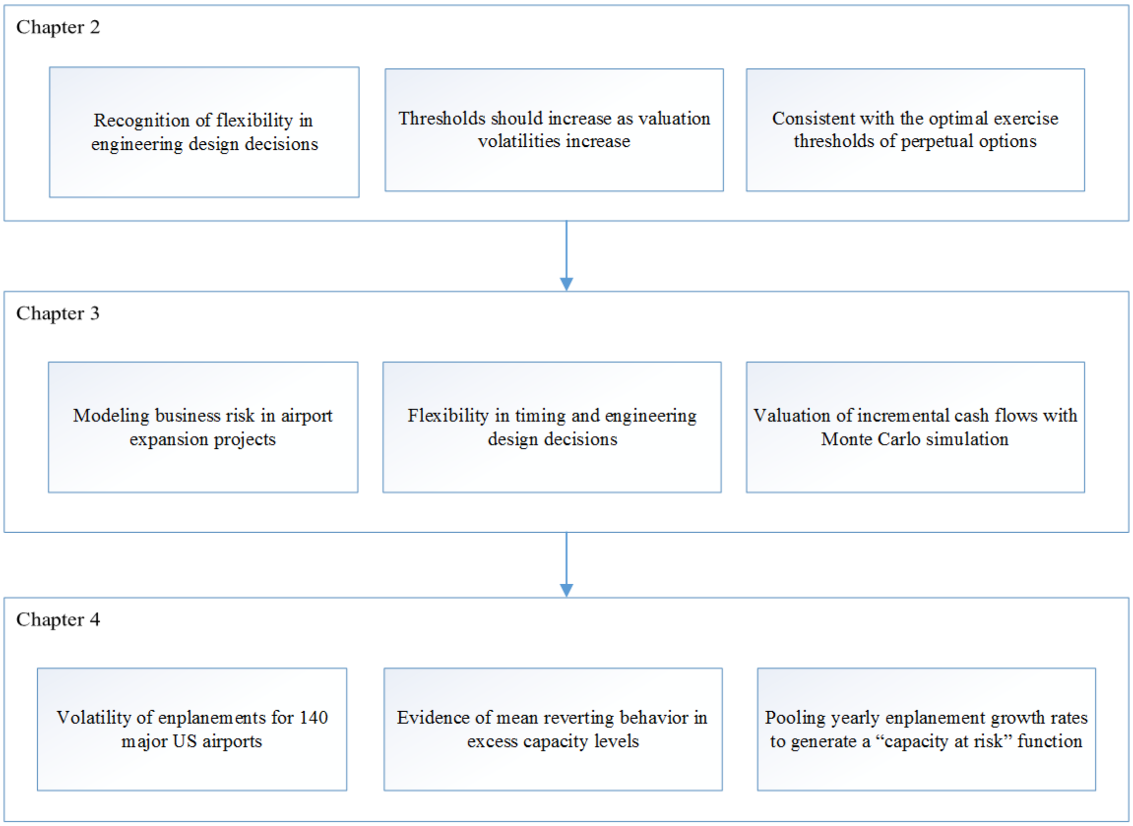
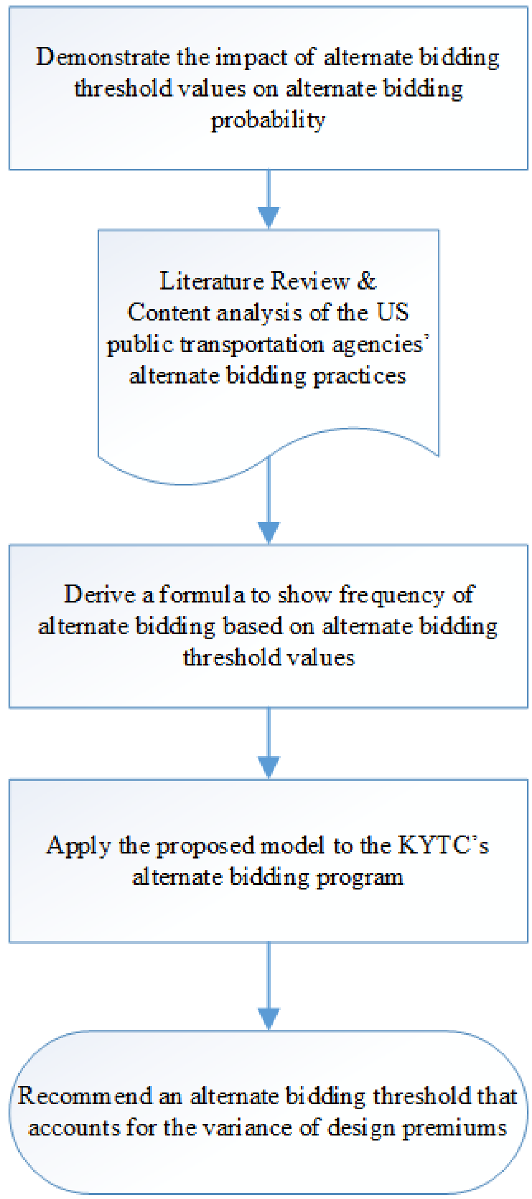


Figure 1-1 Dissertation outline



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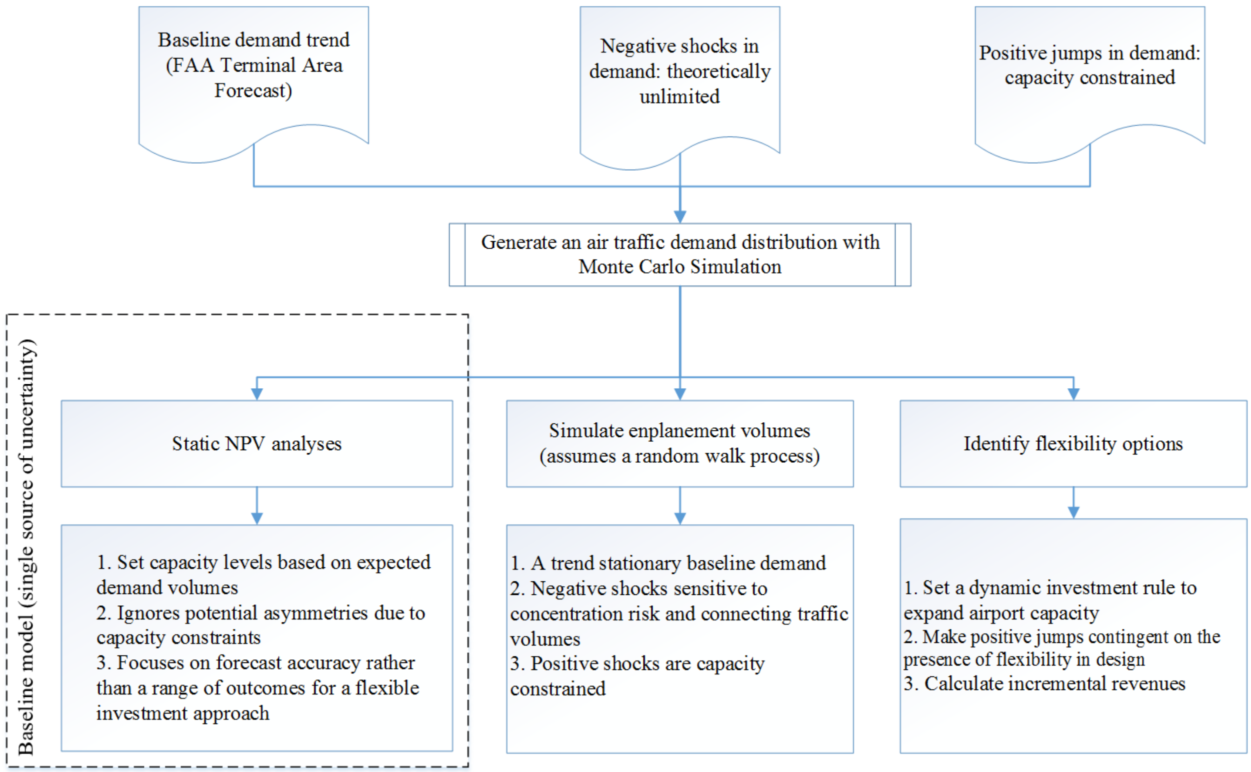

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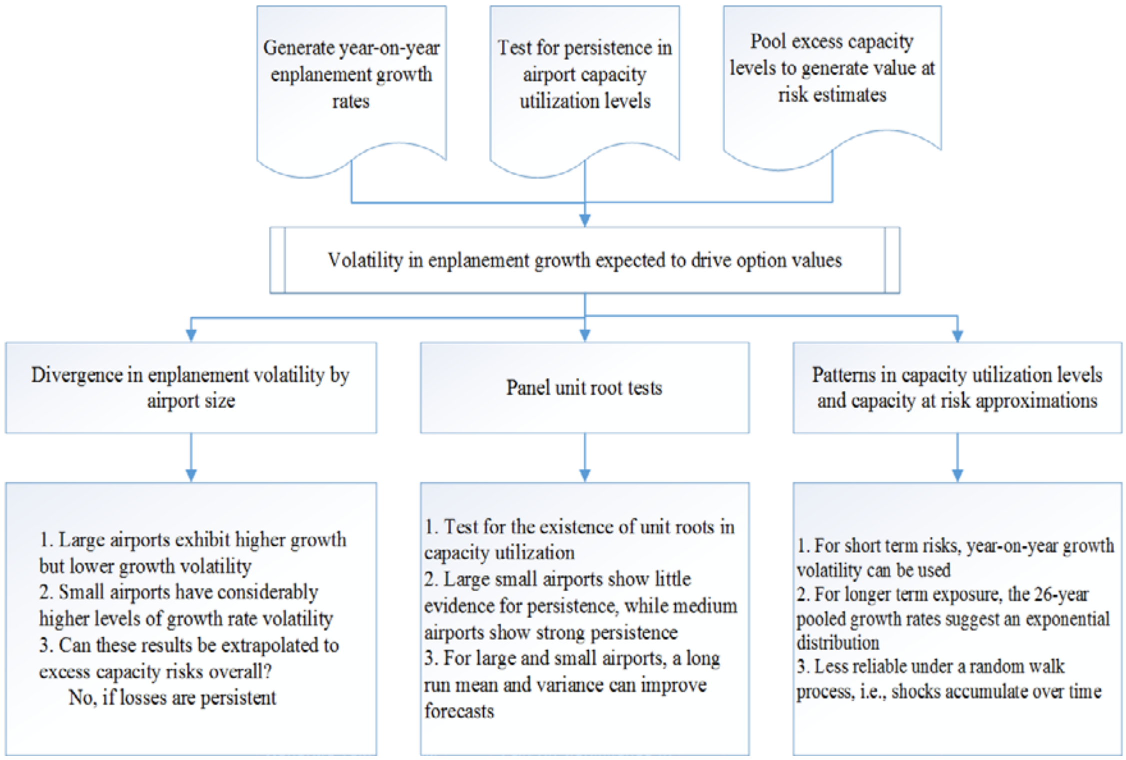

Figure 1-4 Chapter 4 outline

Background

Introduction to key concepts

Flexibility in engineering design

Most engineering decisions are made in isolation, assuming a static stream of cash flows, and ignore decision makers' flexibility to delay investments until additional information becomes available in the future. The ability to adapt engineering designs to account for uncertainty in demand and input costs, for example, can make up a significant portion of a project's value. Some public transportation agencies in the US, for instance, utilize a bidding methodology through permitting contractors to bid on equivalent pavement design alternatives and selecting the lowest bid design alternative. Although the value of this practice has long been understood, the option value of the embedded design flexibility in this bidding method has not been recognized. As Chapter 2 demonstrates, the frequency of alternate bidding has a direct relationship with the agencies' ability to capture the full option value present in competing design methods.

While the traditional discounted cash flow (DCF) analysis assumes a static world in which investment decisions are made on a now-or-never pattern, the real options framework adds value by recognizing the flexibility of the decision makers in choosing only positive cash flow scenarios within time. In other words, managers can prune negative cash flow scenarios and increase the value of the project.

Real options

Real options valuation methodologies provide a well-established framework to quantify the options value of flexibility embedded in several business and engineering applications. There is a considerable amount of work that addresses the relevance of real options valuation approaches for investment under uncertainty (e.g., Dixit and Pindyck (1994), Trigeorgis (1999), Amram and Kulatilaka (1998), Copeland and Antirakov (2003) and Shockley (2007) offer several motivating examples and practical applications). In essence, investments in a real options approach are valued to account for the flexibility of the decision makers in deferring, abandoning and expanding their investments in light of newly available information through the life of their investment options.

This dynamic approach stands in stark contrast to the standard NPV analysis taught in engineering economics textbooks, which assumes investment decisions are made on a now-or-never basis and projects have static valuations. In general, if the investment process creates new options or learning effects, the real options approach speeds up investment when compared with static discounted cash flow. Investments in research and development, in training, new distribution channels, for instance, create new options that can be exercised in the future depending on the market evolution.

Whether capturing a project's real options value defers or expedites a project investment depends on both the nature of the project and on its "moneyness." Projects that provide strategic advantages, for example, can be selected even though a static NPV valuation points otherwise. Irreversible investments that require large initial investments, however, may be deferred in order not to surrender the option's insurance value even though the NPV analysis recommends investing immediately. Such moderately deep in-the-money (with high NPV realizations before accounting for the project's option value) projects would benefit from the resolution of the uncertainty over the best investment approach necessary to improve project's future outcomes. The decision makers may find it more desirable to adopt a wait-and-see approach until such projects become deeply in-the-money. The use of threshold values in triggering the early exercise of options, for instance, has immediate practical value. The ease of which they can be understood and communicated motivates an analysis of their utility when used as rules of thumb in making streamlined investment decisions.

In sum, investments that permit the pruning of negative outcomes through learning effects, lead to the selection of the investment, whereas projects that are sensitive to the resolution of uncertainties in the economy, or other factors tend to favor the deferral of their initiation.

The Binomial model and risk-neutral pricing

Although the Monte Carlo simulation method used in Chapter 3 does not rely on risk neutral pricing, the following discussion is included as background for perpetual options because the derivation of the critical exercise thresholds, which are thought to provide valuable insights into the timing of expansion projects, does rely on risk-neutral pricing. In modeling the uncertainty and the associated value of flexibility, the binomial model is the standard point of departure due to its power in approximating the uncertainty in project valuations (Hull 2006). When combined with the no-arbitrage assumption that drives all valuation models in corporate finance, the binomial model is preferred because it produces log-normally distributed asset values that track the observed behavior of the overwhelming majority of financial assets (Cox et al. 1979).

Binomial decision trees are used to model the uncertainty in investment timing and project present values over time. In this binomial world in which asset prices can go either up or down, by factors of u and d respectively, the passing of each period adds to the complexity of potential paths asset prices can follow. Asset values in the terminal nodes represent the valuation distribution of the project's NPV values under each of the states of nature.

Most discussions on real options valuation offer a simplified binomial model to capture the main dynamics of how a real option's value is derived from the uncertainty in the underlying asset's value. The Black-Scholes option pricing model, which is the standard valuation model for contingent asset values, rests on the fact that one need not be concerned with investors' risk preferences in valuing such options (Merton 1973). In fact, the binomial model is quite powerful in approximating the standard Black-Scholes options model, and despite its set of abstractions and assumptions made in its development, provides the clarity for decision makers to appreciate the value of flexibility in planning and the ability to adapt to new information.

In essence, the binomial model represents a world that has only two outcomes and any derivative written on an asset (e.g., an option on a stock or a real asset such as an infrastructure project) can be replicated perfectly by a tracking portfolio of only two assets—an appropriate combination of a riskless bond and the asset itself.

On balance, despite the powerful insights gained through the use of binomial valuation methods, the following limitations to this line of research exist.

- Limited by the assumption that only one type of uncertainty is present.
- Requires a good understanding of the financial literature on options valuation, which is complex.
- Modeling the uncertainty requires significant verification and fact-checking.

European vs. American Options

In financial terminology, European options refer to contingent claims that can only be exercised at the option's expiration date. European options on real assets may include phased investments that enable a firm to test the feasibility of a new product before starting full-scale production, or, in the case of Chapter 2, the public transportation agencies' ability to observe market prices of competing alternative pavement designs before making decisions on pavement types.

Investments that bear the features of American options, on the other hand, benefit from having the flexibility to decide when to exercise the option. That is, not only can the decision makers obtain new information before they make investment decisions, but they can also choose the best time to invest in a project before the option expires.

Valuation insights in the real options literature

The following discussion provides a short list of common lessons that are expected to guide the paper's real options-based valuation methodology. The paper's findings can be verified by comparing the binomial model's predictions against the following valuation rubrics.

Higher levels of uncertainty increases the value of the option

As with financial options, elevated levels of uncertainty increase the upside potential of options on capital investment projects. That is, higher levels of uncertainty, say, in future air traffic, raise the value of having an expansion option on terminal capacity. Since the expansion options give the planners the ability to limit losses from suboptimal expansion costs, higher uncertainty indicates greater upside potential without the downside exposure under unfavorable demand conditions.

Thus, expansion timing is highly dependent on the uncertainty of future demand parameters. The more uncertain the range of valuations in an airport expansion project, the more value there is in delaying to keep the insurance value of options so that unfavorable demand outcomes can be avoided. Any factor that significantly affects project NPV value, such as interest rates, project funding sources, airline mergers and acquisitions, and so on, is expected to increase the option value derived from the eventual resolution of uncertainty about project value. As such, the paper will seek evidence to show that airport expansions indeed tend to be delayed in uncertain periods.

Options can be costly to acquire

Not all airports have the ability to scale up operations due to several potential constraints. Relaxing such constraints to secure expansion options, however, may impose significant costs for airport planners. Capital investment projects with built-in expansion options, be it the reserve land acquisition or pre-planning to accommodate future growth, can be cost prohibitive for planners to acquire given budget constraints. Whether such costs are worth bearing, in turn, will depend on the value of uncertainty of future demand and thus the option value.

Delaying comes at a cost

Competitive pressures from other airports can also play a role in giving airport planners to gain the first mover advantage (de Neufville 2008). However, even in the absence of competitive pressures, bad expansion timing decisions can lead to lost revenues. In general, factors that tend to increase project NPV can also make delaying costlier. This observation suggests that as the expected payoffs from airport expansion projects increase and the costs of expansion decrease, delaying expansion becomes less desirable. In short, the longer a positive NPV project is delayed, the more its present value diminishes due to lost revenue (i.e., the dividend yield). In time there comes an optimal point where the marginal benefit from deferring expansion equals the marginal cost of losing the project's potential dividends.

Perpetual options and optimal exercise thresholds

This section provides a brief discussion of perpetual options, which offers a consistent analytical model to study the effects of three key input parameters that are used calculate option values: volatility, missed revenues from deferred expansion and the discount rate. Even though the perpetual options model can be thought of as an extension of the Black-Scholes option pricing formula, and it produces the same valuation insights on the effect of volatility, the ability to explicitly specify the optimal exercise threshold for airport activity volumes provides an important tool that is not available in the standard Black-Scholes setting (e.g., see Arkin and Slastnikov (2015) for a recent example of research on perpetual options).

Since the cash flows of most infrastructure projects are effectively insulated from competition and the threat of new entrants, the valuation and timing of projects can be modeled by using a set of valuation inputs equivalent to that employed in a perpetual options framework. As a result, many such projects qualify as natural monopolies with their highly regulated pricing and service offerings, and it is not unreasonable to assume their investment decisions involve high degrees of flexibility in exercising their expansion options at a time of their choosing.

Thanks to the perpetual options framework not only does the decision maker know that as expansion options become more valuable (i.e., the volatility of airport activity levels increase, dividend yields diminish, and the discount rate increases), the optimal exercise threshold in triggering the expansion project also increases. Stated differently, as expansion options become more desirable to hold, they also become harder to exercise. This observation has immediate implications for the valuation of airport expansion projects. For those airports whose flexibility in expanding their capacity matter the most, relinquishing such options also should become harder. This is, in fact, equivalent to the commonly used project screening mechanism based on hurdle rates in standard corporate finance applications (Myers 1984). Conversely, potential option values may explain why certain projects with negative NPV values would be chosen if they involve significant option values.

Perpetual options as a type of real options

When a project's future revenue streams are uncertain, and investments are irreversible, the NPV rule often underestimates project values (Dixit and Pindyck 1994). Instead, the value of a project can be modeled as the sum of the present value of its current earnings as a perpetuity and the present value of its growth opportunities. Given that project owners often have exclusive rights on future revenue streams, infrastructure projects can benefit from a real options approach that adds a growth component to static NPV values. When such growth options can be exercised anytime over the life of the project, and the investment horizon goes to infinity, the valuation problem resembles a perpetual option but with no expiration dates (McDonald 2003). The value of the expansion options increases as the current present value of the project, the time to expiration, the volatility and risk-free rate increase. On the other hand, the value of the option decreases as the project cost and expected revenues from early exercise increase.

Growth options involve opportunities to make further investments and increase project capacity after observing favorable business conditions. They are, thus, similar to holding American call options on the value of projects' potential revenues from the expansion project. The strike price is equivalent to the present value of the expansion costs at the time of option's exercise. Project valuations within an options-based framework capture the uncertainty in future cash flows and explicitly accounts for the nature of uncertainty and its implications. Valuation of real options, thus, treats investment decisions as claims on the revenue streams generated by real assets. When the uncertainty over a project's future cash flows is large, the opportunity cost of outright investment can overwhelm the value of keeping such options open. In fact, the value of growth options can make up a considerable component of a firm's value, in addition to its book value (Hackbarth and Johnson 2015).

As a result, among the most valuable insights gained through the real options framework is the inadequacy of the standard NPV rule, which suggests that positive values of project NPV's should trigger investment even if they are inconsequential but positive. Alternatively, under the flexibility in choosing investment timing and the irreversibility of investments, it is shown that managers require substantially higher levels of project values before the insurance value of investment options against subsequent drops in project values can be given up in return for immediate cash payouts from the project's revenue stream. In fact, this additional hurdle project value can be derived explicitly by maximizing the call option value representing the firm's growth opportunities. Uncertainty in project values, a necessary factor for the presence of option values, for instance, increases the value of a project's growth opportunities but reduces the frequency of options' exercise due to increased threshold levels. Consequently, while demand uncertainty for a project may increase the option value embedded in the project, it may also make the project more cautious in expanding its investment activity.

Derivation of optimal investment thresholds

The Black-Scholes formula assumes that an option has a finite life and is exercised only at expiration. For options that never expire and can be exercised anytime, however, the relatively complex valuation methodology of American options can be simplified and leads to the derivation of an optimal exercise threshold as explained further below.

The finite lives of American options make it difficult to characterize an optimal exercise strategy (McDonald and Siegel 1986). Although Monte Carlo simulations can be used to value American options, it can be fairly complicated. Instead, the binomial model is the preferred method. For an American option with a dividend-paying underlying, the optimal exercise price declines as the option approaches expiration. This shrinking option value over the life of the option considerably complicates the derivation of a valuation formula. However, this complexity can be overcome by the expirationless feature of perpetual options because such options have constant time to expiration—infinity. Since the optimal exercise price of a perpetual option is time-invariant, the optimal exercise strategy implies the calculation of the right asset threshold and exercising the option as soon as the threshold barrier is breached.

When the underlying cash flows are uncertain, optimal investment timing can be determined by modeling the evolution of project value over time. The optimal investment strategy then is defined by a critical asset value threshold that, when reached, would trigger investment.

The value of a project under uncertainty is assumed to be distributed lognormally and follows a random walk across time. Thus, the project value, A, follows a geometric Brownian motion shown in Equation 1-1.

$$\frac{dA}{A} = (\mu - \delta)dt + \sigma dz \qquad \textbf{Equation 1-1}$$

where μ is the expected return on the asset value, δ, is the dividend rate, and dz represents a Wiener process.

The computation of an optimal exercise threshold for perpetual options rests upon the valuation of $1 payable when the asset price reaches a level, H (McDonald 2003). The present value of this $1 payout when the asset reaches the threshold H is called the "barrier present value." Assuming the current asset level is below the threshold level for a call option on an expansion project, for instance, the barrier present value is calculated as follows.

$$\textit{Barrier present value} = \left(\frac{A}{H}\right)^{h_1} \qquad \textbf{Equation 1-2}$$

where A is current asset value, H is the threshold at which option should be exercised and h_1 is defined as

$$h_1 = \frac{1}{2} - \frac{r-\delta}{\sigma^2} + \sqrt{\left(\frac{r-\delta}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2r}{\sigma^2}} \qquad \textbf{Equation 1-3}$$

For perpetual American call options with strike price of X, the payoff at exercise is $(H - X)$. Given the previous barrier present value formula, the value of receiving at exercise (when A reaches X) is

$$(H - X)\left(\frac{A}{H}\right)^{h_1} \qquad \textbf{Equation 1-4}$$

The optimal threshold level for exercise is the asset price at which the value of keeping the option alive, i.e., its insurance value against potential drops in asset value in the future, equals the expected value of dividends after the option's exercise. This optimal level can be found by differentiating the expected payoff formula at exercise with respect to *H*, setting the derivative equal to zero, and solving for *H* (Equation 1-5). As expected, when the asset has no dividend yield, $\delta = 0$, then the perpetual call reduces to an American call in that it is never optimal to exercise, $H^* = \infty$ (Equation 1-6).

$$\boldsymbol{H^* = X\left(\frac{h_1}{h_1 - 1}\right)}$$ **Equation 1-5**

$$\boldsymbol{Price\ of\ perpetual\ call = \left(\frac{X}{h_1 - 1}\right)\left(\frac{h_1 - 1}{h_1}\frac{A}{X}\right)^{h_1}}$$ **Equation 1-6**

The effects discount rate, volatility, and dividend yield on the optimal investment threshold

Discount rate $(\boldsymbol{r})$: Higher values of expected rate of return on project assets increase the option value, thus imposing a more stringent threshold value for option's exercise. Higher discount rates diminish the present value of the investment cost, making the opportunity cost of exercising the option high. In turn, lower discount rates induce more investing by reducing the critical hurdle levels necessary to exercise the option. As Figure 1-5 illustrates, increasing the discount rate makes it harder to invest (optimal investment threshold also increases).

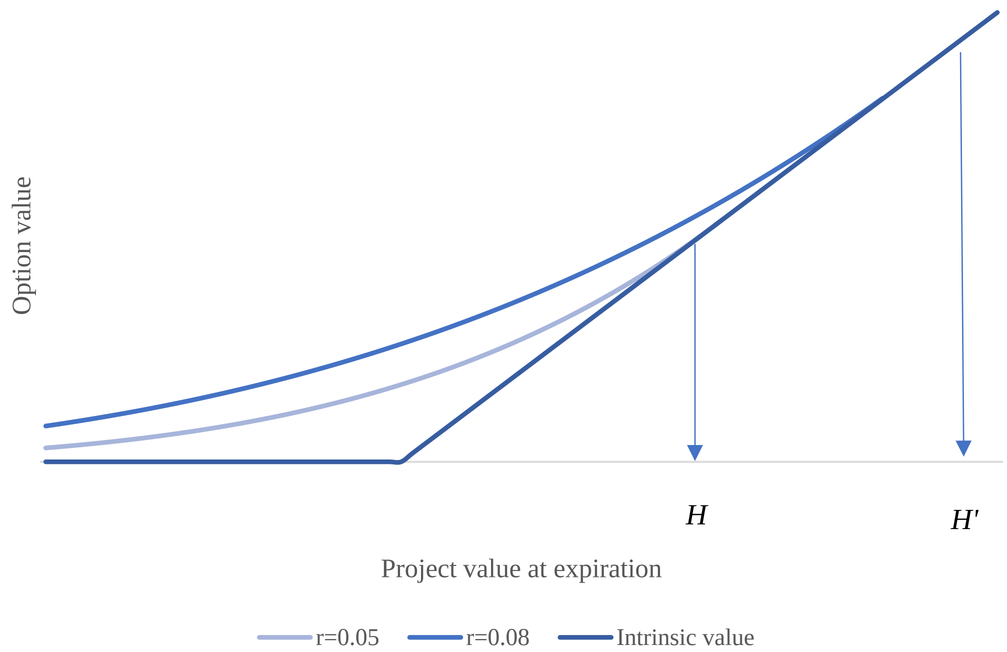

Figure 1-5 Effect of increasing discount rate on the optimal exercise threshold *(H)*

The volatility of project values(σ): Higher volatility of asset valuations leads to higher threshold levels due to increased option values. As the value of growth options is worth more along with increasing volatility of project values, the opportunity costs of investing also increase, thus making investment harder to justify. This results in a more conservative investment strategy with higher threshold levels. Conversely, lower volatility levels encourage lower threshold levels, making the exercise of the option more likely. Figure 1-6 indicates that increasing the volatility of project values makes harder to exercise expansion options (optimal threshold also increases).

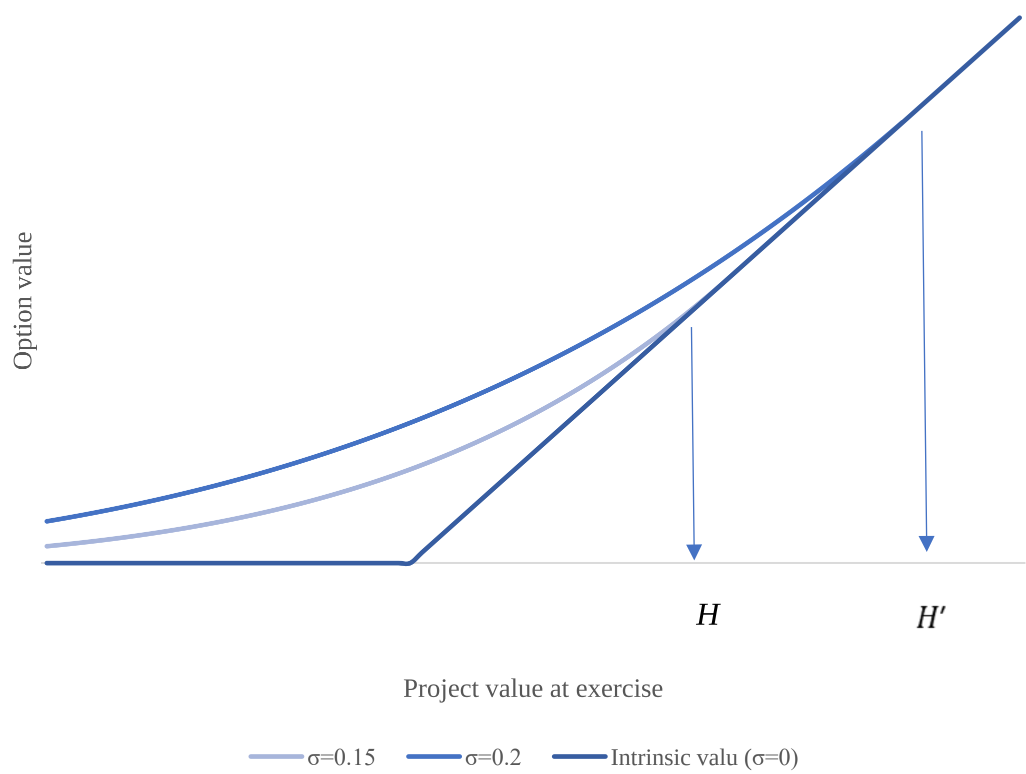

Figure 1-6 Effect of increasing volatility on the optimal exercise threshold *(H)*

Dividend yield (project cash payouts) ($\boldsymbol{\delta}$)**:** The presence of cash payouts with early exercise of the option introduces the crucial tradeoff mechanism that represents the opportunity cost of keeping the investment option alive. Since the option values decrease as the dividend yields increase, lower critical threshold values encourage higher volumes of investing. As the dividend rate approaches zero, option's exercise becomes less likely. Figure 1-7 shows that an increasing dividend yield rate makes easier to invest in expansion options (optimal threshold decreases).

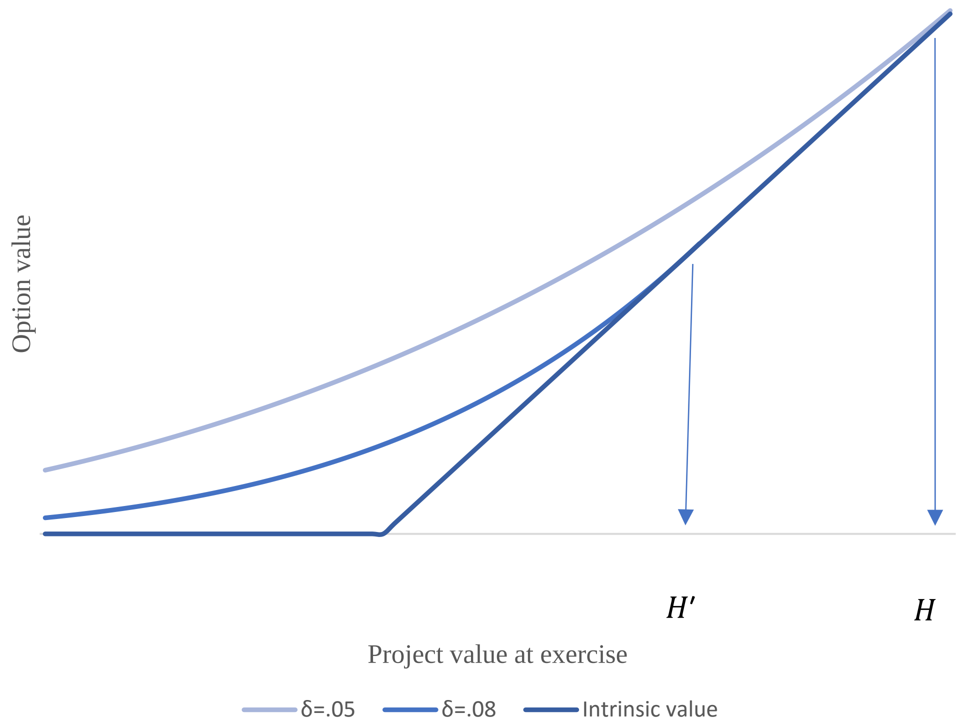

Figure 1-7 Effect of increasing dividend yield on the optimal exercise threshold *(H)*

Finally, higher investment costs (X) reduce option values, resulting in higher threshold values for option's exercise, while lower exercise costs make investments easier to justify with lower corresponding critical investment thresholds.

The next two chapters that follow illustrate how valuation insights from a perpetual options framework can contribute to a better understanding of the connection between increasing volatility and optimal exercise thresholds. First, the ad-hoc NPV thresholds used the state transportation agencies are shown to ignore the role of volatility when choosing among competing design alternatives, which arguably leads to too many outright design choices and nonoptimal utilization of embedded flexibility options. Instead, when the uncertainty over which design alternative would, in fact, be the lowest cost method increases, the paper's findings suggest that a higher threshold should be adopted. Next, building on the observation that as options become more desirable to hold, exercising them should also become harder, Chapter 3, introduces a mechanism to make more guarded expansion decisions, (i.e., decision makers can wait longer to ensure that growth trends in demand are indeed sustainable).

CHAPTER 2. IMPACT OF LIFE-CYCLE COSTS THRESHOLD CRITERIA IN THE ALTERNATE DESIGN PAVEMENT BIDDING PRACTICES OF PUBLIC TRANSPORTATION AGENCIES

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Karaca, I[1]; Gransberg, D.D[2].; Buss, A[3].

Abstract

This paper proposes a model that enables DOT policy makers to quantify the expected volume of projects that will qualify for letting in their alternate design/alternate bid (ADAB) pavement bidding programs. Current guidance on alternate bidding recommends a fixed percentage as the life cycle cost (LCC) threshold criterion to determine whether pavement selection decisions should be made through ADAB bidding practices. The paper's analysis shows that the fixed LCC threshold percentage approach may have considerable shortcomings. Instead, a dynamic threshold value is proposed that can subsequently be calibrated by agencies, based on the desired size of their ADAB programs. The paper argues that since the costs of equivalent pavement designs exhibit considerable variation due to various project and agency-level factors, agencies' desired alternate bidding program levels can only be achieved by taking into account the variation of equivalent pavement type costs as opposed to the current blanket threshold percentage. The paper demonstrates with Kentucky Transportation Cabinet (KYTC)

[1] Corresponding author. Ph.D. candidate. Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 50011. E-mail: ikaraca@iastate.edu

[2] Professor of Civil Engineering, Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 5001. E-mail: dgran@iastate.edu

[3] Assistant Professor of Civil Engineering, Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 5001. E-mail: abuss@iastate.edu

ADAB data that modeling this variability through a random distribution is not only a close representation of actual agency data, but it also distils those variables that drive a large share of the complexity in agency ADAB policy decisions. The paper's primary contribution is the derivation of a direct mathematical relationship between equivalent design premiums, agencies' threshold criteria, and alternate bidding program volumes that can be used by DOT policy makers to better manage their ADAB programs.

Introduction

The controversy over pavement type selection is both longstanding and complex (Hennings 2013, Anderson and Russell 2001). The consensus solution is to include an analysis of pavement life cycle costs (LCC) in the design process, leading to selecting the alternative that minimizes LCC (FHWA 2009, Walls and Smith 1998). That process, however, ignores the impact of construction material volatility i.e. actual contract pricing, on the day a pavement project is let since it is based on pricing "assumptions made during the [pavement type] evaluation/selection process years before letting" (Lenz 2010). To further exacerbate the controversy, the ability to generate truly equivalent pavement designs has been in question ever since the idea of alternate pavement bidding schemes were authorized under the FHWA's Special Experimental Project 14 (SEP-14) in 2000 (FHWA 2015). On the bright side, there seems to be agreement that the use of alternate design/alternate bid (ADAB) procurement procedures reduces pavement prices by increasing the number of eligible bidders as both asphalt and concrete paving contractors can bid on the same ADAB projects (Temple et al. 2004, ODOT 2004, Newman 2008, Mikesell 2012). It is because of ADAB's documented benefits that interest in identifying effective practices and procedures endures.

Therefore the objective of this paper is to fill a documented gap in the body of ADAB knowledge by proposing and demonstrating a rational, LCC-based method for identifying those pavement projects that are good candidates for ADAB procurement on a programmatic basis. With the advancement of the Mechanistic-Empirical Pavement Design Guide (MEPDG) methodology, agencies' ability to achieve equivalent designs has improved dramatically (Pierce and McGovern 2014). This provides new incentives to open bidding to both industries and experience cost savings for the agencies. Alternate bidding programs can realize savings to agencies by giving them the ability to make final pavement design decisions where there is no clear preferred design alternative and market prices for different design types are volatile (Temple et al. 2004).

Agency decisions to select ADAB projects have important consequences and potentially impose sizeable opportunity costs for the agencies. Ideally, every pavement type selection decision could benefit if it were made by comparing real-time market prices for competing alternatives on the day of letting. However, using alternate bidding on every project has the potential to increase project development costs due to increased cost of producing equivalent designs, and the associated engineering effort in generating a set of plans and specifications for each alternative.

Although such costs could become marginal after alternative designs are established for agencies' typical pavement designs, the initial costs to implement an alternative bidding program can still be substantial. Further, adopting an alternative bidding program requires the agency to develop a locally acceptable method to calculate an LCC-based adjustment factor, which is the recommended approach to compare competing alternatives with differing future maintenance and rehabilitation costs (Hallin et al. 2011). Such challenges leave agencies facing a tradeoff in weighing the expected benefits of an alternative bidding program against the costs of administering such award practices. Figure 2-1 illustrates the role of alternate bidding in pavement type selection decisions.

There is currently limited guidance on when to use alternate bidding. A commonly accepted practice is to call competing designs equivalent if they provide a similar level of performance and their Net Present Value (NPV) is within a specified threshold value of each other (FHWA 2012). FHWA guidance on LCC thresholds suggests 10% as an appropriate level, i.e., the LCC of one alternative is lower than 10% of the LCC of the other (FHWA 2012). A common metric for assessing similar service levels, for instance, is to verify whether the expected IRI values of competing alternative pavement types remain in comparable condition over the analysis period (IRI < 95 inches/mile for good condition, IRI < 170 inches/mile for fair condition, etc.) (FHWA 2012). Once design equivalence is established among the competing alternatives and their LCCs are calculated, it is expected that those alternatives that fall within the threshold margin of 10% are too similar in life-cycle costs to permit an outright decision to be made for a preferred alternative.

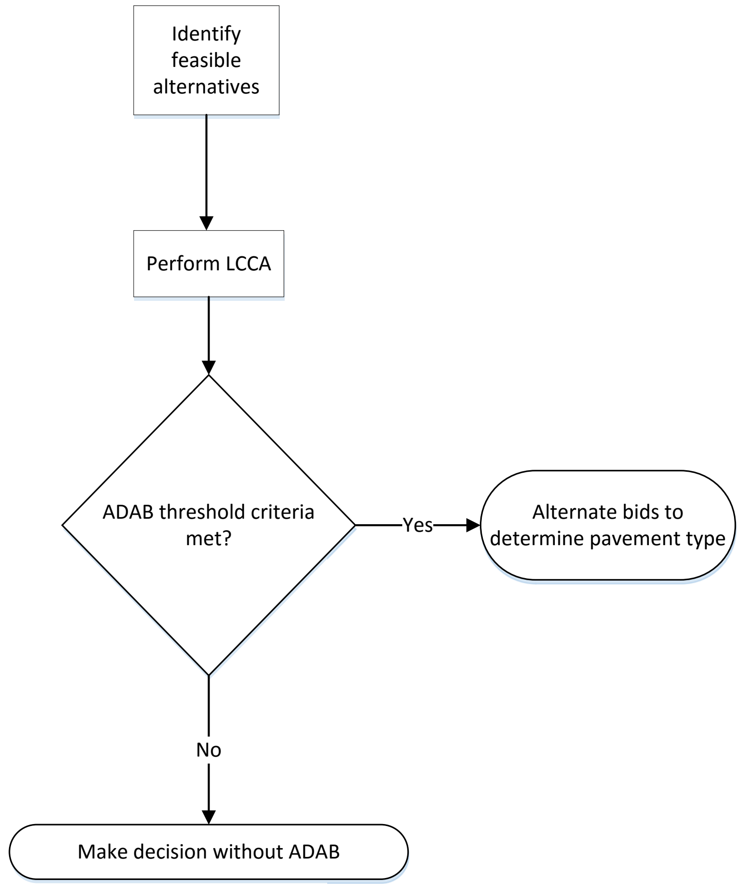

Figure 2-1 Alternate bidding and pavement type selection decisions

There is no agreement on LCC threshold values for alternate bidding (Hallin et al. 2011). This fluid nature of setting an LCC-based cutoff level is reflected in the agencies' ADAB practices. A content analysis in agency ADAB policies has found that the threshold levels can range from 10% to 20% (MDOT 2016, ODOT 2014, KYTC 2007). Other types of thresholds, such as roadway area and functional classification, are also common among agencies to identify qualifying projects. At this writing, there has been no formal research to establish what variables should be included in the threshold value setting decision nor the outcomes of establishing different threshold values, as well as identifying the factors that influence the outcomes.

The FHWA calls the 10% threshold value “appropriate due to the uncertainty associated with estimating future costs and timing of maintenance and rehabilitation” (FHWA 2012). However, such guidance, while focusing on the uncertainty over the LCC input variables, falls short of addressing the linkage between threshold levels and their impact on how many projects would be included under alternate bidding. Clearly, higher threshold levels imply a larger number of qualifying ADAB projects. Conversely, lower threshold levels make it more restrictive for potential candidate projects to be considered in the alternate bidding program.

The main tradeoff in the selection of the threshold value is the costs associated with alternate bidding and testing the true market costs of alternate pavement designs before a decision can be made. Ideally, if alternate bidding were cost free, all projects could be let using alternate bidding, which corresponds to a no threshold case. As the threshold level reduces to zero, qualification of projects for the ADAB program becomes increasingly restrictive, and fewer projects would be expected to let under alternate bidding.

Theoretically, agency’s discretion in setting threshold values ranges from zero, where no alternate bidding is allowed, to infinity, where all projects are awarded through alternate bidding. Under the zero-threshold case, the agency’s lowest cost alternate pavement design is assumed to be the most economical alternative in all cases. However, this approach also exposes the agency to the highest risk of foregoing the benefits of alternate bidding, as the market cost of the competing alternative remains untested. This was the situation before SEP-14 authorization to experiment with ADAB.

Background

In response to the growing adoption of ADAB practices among the state agencies, the FHWA endorsed the use ADAB methods in 2012 (FHWA 2012). It is now clear that many states that use ADAB procedures have recorded tangible benefits from the practice (INDOT 2009, ODOT 2004, Youngs and Krom 2009). The main benefits include reduced project costs from increased competition (Temple et al. 2004). Agency policies on ADAB procedures show a significant degree of variation of across states (Crawford 2014, Jeong et al. 2012).

Alternative pavement designs are compared based on common pavement life-cycle maintenance and rehabilitation strategies (Wall and Smith 1998). To achieve similar serviceability performances covering the selected analysis period, both initial design/construction costs and the future cost of maintenance/rehabilitation activities must be specified. The development of realistic LCC analysis that is consistent with local policies and procedures is crucial to compare alternatives based on LCCs.

There are two main groups of considerations that need to be addressed before alternates can be compared. First, the underlying assumption of all ADAB methods is the presence of design equivalence, without which competing alternates cannot be meaningfully compared. Adjusting for the differences in LCCs thus becomes an important consideration for alternate bidding practices.

Secondly, ADAB can be expected to be most applicable to the pavement type selection decisions when the expected LCCs of competing alternatives are reasonably close to one another and when there is not a preferred pavement type among the competing alternatives. While there is no consensus on a single threshold level among the state transportation agencies, thresholds in practice range from 10% to 20% (Hallin et al. 2011).

Although agencies have differing approaches to achieving design equivalence among competing alternative pavement designs, the expected benefits of ADAB depends greatly on the design equivalence of competing alternatives. Given the design requirements on traffic level, reliability and service life, the pavement service levels are expected to sustain comparable levels of service over the period of the pavement design life. A similar level of service can be measured by the alternative designs' performance over the analysis period based on models that realistically reflect agency conditions. Since competing design methods often have unequal traditional design periods, the performance period should be made equal by including at least one major rehabilitation cycle (FHWA 2012).

The specification of similar service levels over the common performance period depends on the underlying maintenance and rehabilitation strategy assumptions for each alternate. Each strategy must reflect realistic agency-level maintenance and rehabilitation costs, calibrated to simulate the pavement service levels with associated future costs (Von Quintus and Moultrop 2007). Since the timing and nature of maintenance and rehabilitation activities drive LCCs, as well as the resultant bid adjustment factors in comparing alternative pavement types, such costs need to be included the selection process for a project's pavement design. A review of recommended maintenance and rehabilitation strategies can be found in the NCHRP Report 703, Guide for Pavement Type Selection (Hallin et al. 2011).

Alternate bidding and threshold criteria

Since the goal of the analysis is to demonstrate that the number of qualifying ADAB projects is a direct function of threshold values, the point of departure is the distribution of project sizes within a given agency. Commonly, agency design type decisions involve at least two types of pavement designs (for example, hot mix asphalt (HMA) and Portland cement concrete (PCC) pavement types).

Without loss of generality, the default pavement design is called Alternative 1, and the competing pavement type Alternative 2. Figure 2-2 shows the probability distribution of the expected project costs within an agency when a default pavement type (Alternative 1) is selected for all projects. Reflecting the cost difference between alternative pavement designs, Alternative 2 is assumed to be a linear transformation of Alternative 1 with a premium coefficient (P) that varies randomly. The expected project costs under Alternative 2 can thus be calculated once the default pavement type costs and equivalent design premium distributions are known. Since the alternate bidding decisions are typically based on the net present value (NPV) value of LCCs, in what follows, the terms “cost” and “LCC” are used interchangeably.

Let A_d be the set of all expected LCCs of agency projects ($NPV_{Alt\ 1}(x)$) if built under the default pavement type alternative (Alternative 1). Similarly, define A_c as the set of the expected project costs ($NPV_{Alt\ 2}(x)$) under the competing pavement design (Alternative 2) as follows:

$$\boldsymbol{NPV_{Alt\ 2}(x) = P \times NPV_{Alt\ 1}(x)} \qquad \textbf{Equation 2-1}$$

This analysis assumes the agency project costs under the default pavement design alternative to be lognormally distributed. As with many price distributions, lognormal distribution provides a realistic fit for project sizes, primarily because, unlike the normal distribution, it does not permit negative values for project sizes, and has been found by previous research to be the best fit for pavement projects of all types (Tighe 2001). However, it should be noted that any other type of distribution that does not allow negative project costs could also be used, since the following discussion holds independently of the assumed project cost distribution.

Let the equivalent design premium of the competing design type (P) be equal to a normally distributed random variable with mean (p) and standard deviation (σ_p):

$$\boldsymbol{P \sim N(p, \sigma_p{}^2)}$$ **Equation 2-2**

The preceding formulation of competing pavement design costs allows a realistic modeling of equivalent design alternatives. Rather than assuming a fixed premium for each competing design type over the default type, it is acknowledged that premiums over the default type costs are variable, and depending on the standard deviation of alternative pavement premiums (σ_p), the competing alternative costs are permitted to be lower than the default alternative's costs. Although alternative equivalent design premium distributions could be also considered, the normal distribution provides a reasonable fit to agency data based on a list of alternate bid tabulations provided by the Kentucky Transportation Cabinet (KYTC) (Looney 2010).

As noted earlier, agency ADAB decisions are based on a comparison of LCCs among different pavement designs. Since this comparison is equivalent to the LCC ratio of design alternatives, following the FHWA's convention (higher cost alternative over the lower cost alternative), the LCC ratio for any project of x is computed by Equation 2-3.

$$\boldsymbol{LCC\ Ratio}(\boldsymbol{x}) = \frac{\boldsymbol{NPV_{Alt\ 2}}(x)}{\boldsymbol{NPV_{Alt\ 1}}(x)}$$ **Equation 2-3**

Clearly, given the definition in Equation 1, the LCC ratio reduces to the equivalent design premium (*P*). Put differently, the LCC ratio of competing alternatives in ADAB decisions can be interpreted as the expected premium for the competing pavement designs (Equation 2-4).

$$\boldsymbol{LCC\ Ratio} \sim \boldsymbol{N}(\boldsymbol{p}, \boldsymbol{\sigma_p}^{\mathbf{2}})$$ **Equation 2-4**

This finding provides the basic framework to study the impact of LCC thresholds in alternate bidding, and as will be shown shortly, it greatly simplifies the analysis, enabling the analyst to focus on the two critical variables of the equivalent design premium distribution—the expected premium for the alternative design type (*p*), and its standard deviation (σ_p). The probability of project LCCs meeting the ADAB threshold criteria can be then calculated as shown in Equation 2-5.

$$\boldsymbol{Pr}(\boldsymbol{T} \geq \boldsymbol{LCC\ Ratio} \geq \mathbf{1}) = \boldsymbol{F}(\boldsymbol{T}) - \boldsymbol{F}(\mathbf{1})$$ **Equation 2-5**

F(T) and *F(1)* stand for the cumulative density function of the normal distribution for the two critical values (the threshold level, *T*, and *1*, respectively). Given the normal distribution assumption for the *LCC Ratio*, the probability of including agency projects in ADAB (Equation 2-5) can be rewritten as seen in Equation 2-6.

$$\boldsymbol{Pr}(\boldsymbol{Alternate\ Bidding}) = \boldsymbol{F}\left(\frac{\boldsymbol{T}-\boldsymbol{p}}{\boldsymbol{\sigma_p}}\right) - \boldsymbol{F}\left(\frac{\mathbf{1}-\boldsymbol{p}}{\boldsymbol{\sigma_p}}\right)$$ **Equation 2-6**

As Equation 2-6 indicates, the frequency of agencies' ADAB practices is a function of three variables:

1. *T*, the ADAB threshold value;
2. *p*, expected equivalent design premium for competing pavement type; and
3. σ_p, the standard deviation of equivalent design premiums.

Setting threshold levels in alternative bidding to reap the benefits of increased competition from multiple industries, thus, cannot be accomplished without taking note of the close interaction between these three factors.

Three major conclusions immediately follow Equation 2-6. First, the probability of meeting ADAB criteria is a strictly increasing function of the threshold value, *T*. Second, the expected equivalent design premium for the higher cost alternative, *p*, has a generally negative impact on the frequency of meeting the ADAB threshold criteria. That is, for most realistic values of *p*, the higher the expected premium levels, the lower the ADAB probability. Third, ADAB probability is a strictly decreasing function of the standard deviation of the equivalent design premium, σ_p.

The finding that ADAB probability increases with higher threshold values is both intuitive and expected. Agencies that have no threshold levels for ADAB are expected to practice an all-inclusive ADAB program. The next two findings, however, to our knowledge, have not been recognized in the literature thus far. Together they show that ADAB threshold levels should be determined by considering the relative values of expected equivalent design premiums and their statistical variation. Illustrating this point will be the focus the following discussion.

Sensitivity of alternate bidding thresholds to equivalent design premiums

This section will consider an example to illustrate the sensitivity of ADAB thresholds to equivalent design premium distributions. Although available data to generate typical project cost distributions for equivalent alternative designs is sparse, the following discussion is based on distribution parameters obtained from a sample of project bids under the KYTC's ADAB program. This data was selected merely because it was both cogent and easily accessible. The KYTC was an early SEP-14 ADAB experimenter, and the results of their pilot projects were generally representative of those observed in other ADAB SEP-14 applicants. Figure 2-2 illustrates the probability density functions (PDF) for a representative agency's project costs. The set of all project LCCs under the default (A_d), and the competing pavement designs (A_c) are labeled as Alternative 1 and Alternative 2 LCCs, respectively. Note that the relationship between the default and competing design costs were previously defined in Equation 2-1.

The calculated model parameters are shown in Equation 2-7. The KYTC ADAB program witnessed equivalent design premiums, P_K, over the lowest cost alternative type at an average of 10 percent ($p = 0.10$) and a standard deviation of 11 percent ($\sigma_p = 0.11$).

$$\boldsymbol{P_K \sim N(0.10, 0.11^2)} \qquad \textbf{Equation 2-7}$$

As expected, the average project cost under the competing pavement type alternative is 10 percent higher than the average project cost under the default pavement design alternative ($10 million vs. $11 million in Figure 2-2). The threshold value, *T*, was also assumed be 10 percent. Note that although the threshold value and the expected equivalent design premium were assumed to be both 10 percent in the baseline scenario, they need not be equal. In fact, the upcoming analysis will vary the equivalent design premium to examine the sensitivity of alternate bidding probability to this variable.

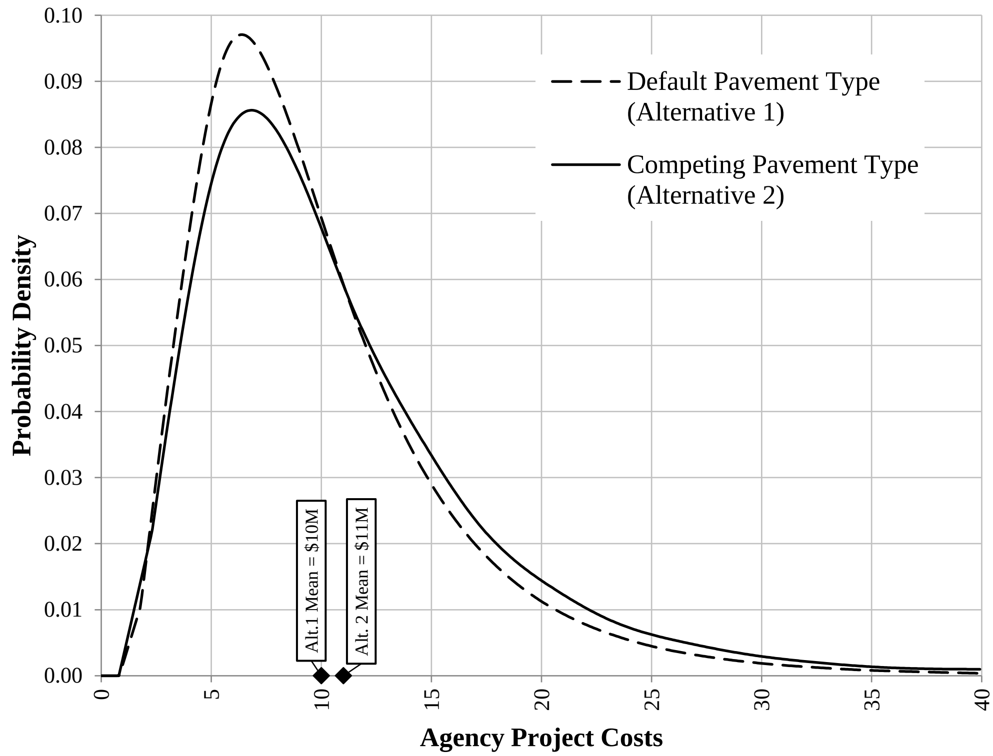

Figure 2-2 Project cost distributions under multiple pavement type alternatives

The probability of the agency's projects to meet the ADAB threshold criteria can be then calculated as

$$\boldsymbol{P(Alternate\ Bidding) = F\left(\frac{1.1-1.1}{0.11}\right) - F\left(\frac{1-0.1}{0.11}\right)} \qquad \textbf{Equation 2-8}$$

$$= 0.5 - 0.182$$

$$= 0.318$$

The result of Equation 2-8 (31.8 %) is equivalent to the region delineated by the two vertical lines in Figure 2-3. The area above the lower bound of the LCC Ratio, where both alternate LCCs are equal, and below the threshold value of 10 percent ($1 \leq LCC\ Ratio \leq 1.10$)

captures the share of agency projects that will be screened for potential alternate bidding. In this example, approximately 32 percent of the agency projects are expected to meet the ADAB threshold criteria. This result can be of immediate use to the agency as policy makers calibrate the agency's ADAB threshold in an effort to balance the anticipated costs and benefits of alternate bidding practices.

Figure 2-4 and 2-5 illustrate the sensitivity of the expected ADAB program size as the expected equivalent design premium levels (p) and its standard deviation (σ_p) change. As the equivalent design premium characteristics are both allowed to increase, the ensuing reductions in expected ADAB program size corroborate the major findings identified previously. Figure 2-4 shows the effect of an increased level of equivalent design premium of 15 percent. Due to the rightward shift in the probability density function due to this increase, the ADAB region for qualifying projects shrinks to 23.8 percent. Similarly, Figure 2-5 demonstrates the effect of higher volatility in the LCCs of equivalent alternative designs.

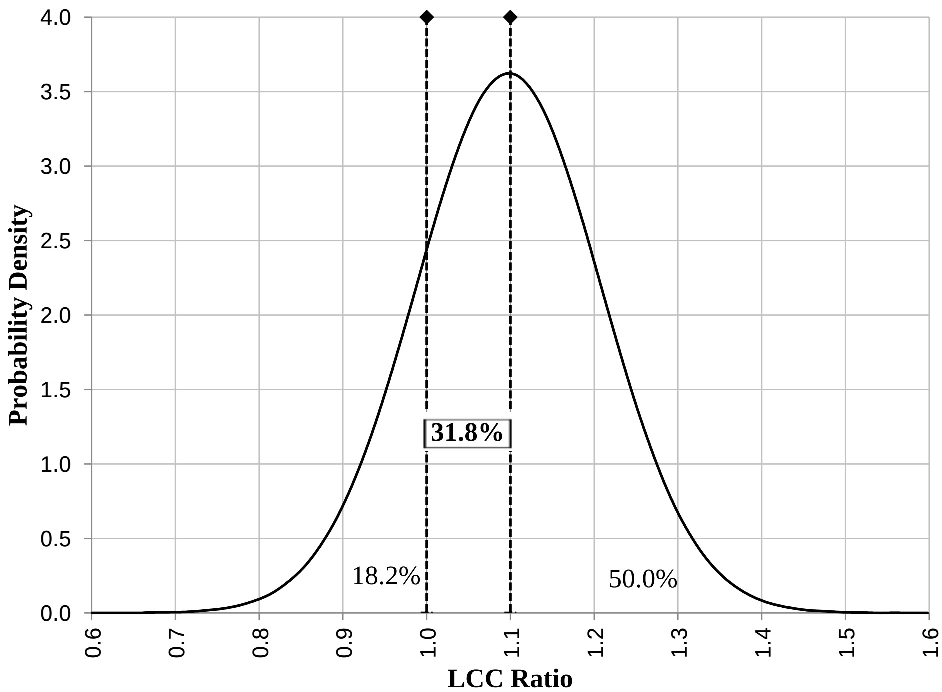

Figure 2-3 **LCC ratio PDF (Baseline Case: $T = 10\%$ $p = 10\%$; $\sigma_p = 11\%$)**

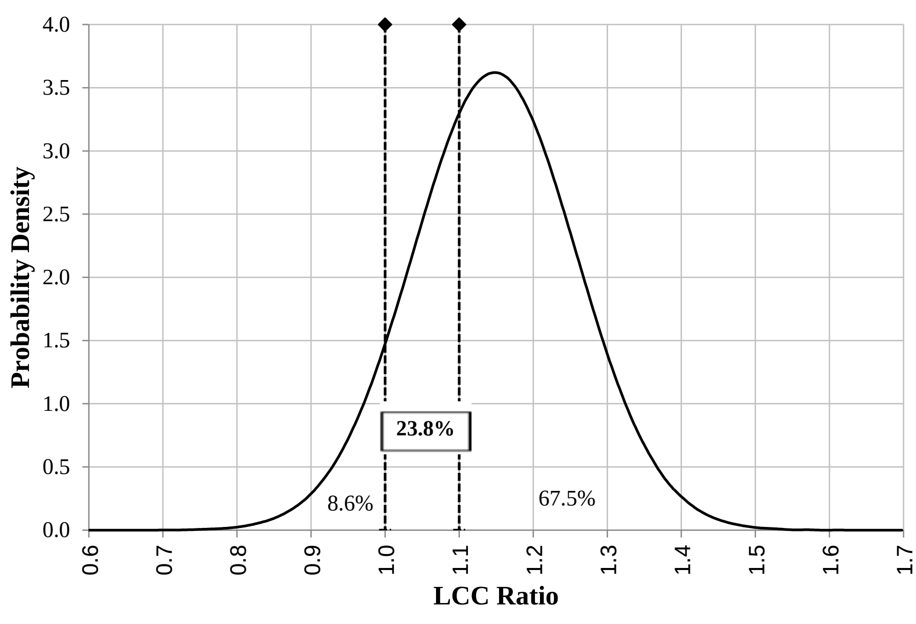

Figure 2-4 LCC ratio PDF (High Expected Premium: $= 10\%$; $p = 15\%$; $\sigma_p = 11\%$)

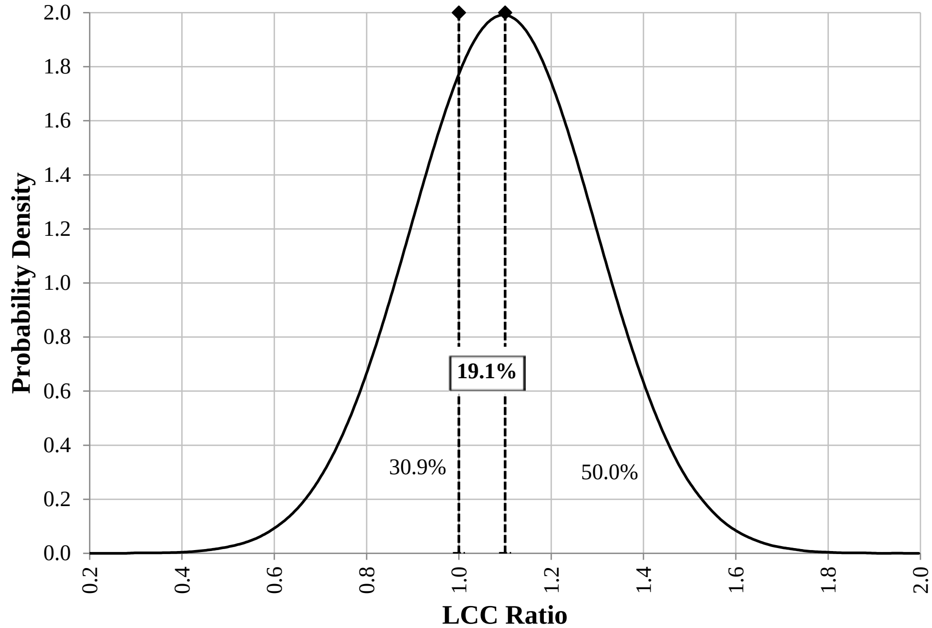

Figure 2-5 LCC ratio PDF (High Premium Variation: $= 10\%$; p $= 10\%$; $\sigma_p = 20\%$)

Increased dispersion in equivalent design premiums reduces the ADAB probability to 19.1 percent. The policy implication of these observations for agencies is clear. If the agency's goal is to maintain the baseline 32-percent ADAB program volume, the ADAB threshold level must be increased. In this example, increasing the threshold percentage for the two scenarios considered to approximately 13 and 17 percent, respectively, would ensure the original 32-percent ADAB volume under the baseline scenario.

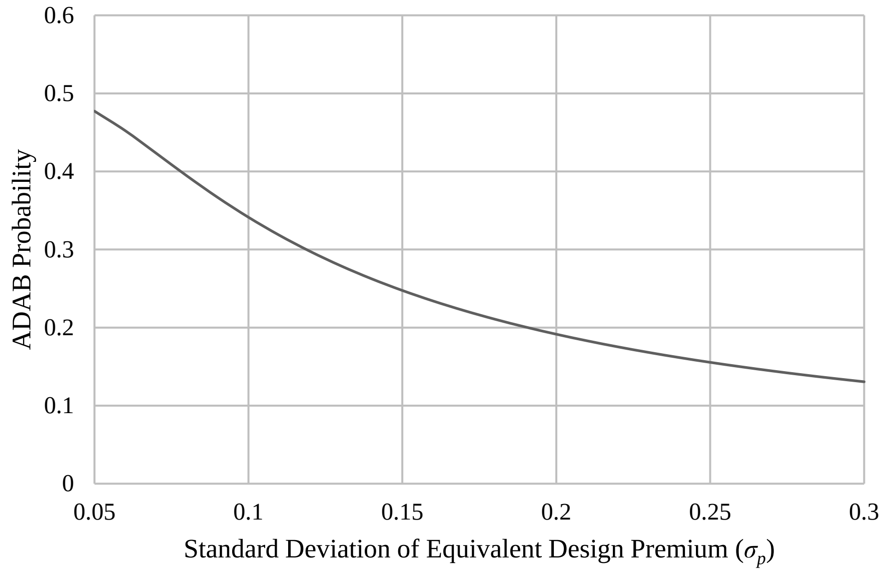

Figure 2-6 Sensitivity of ADAB probability to premium variation ($\boldsymbol{T = 10\%}$; $\boldsymbol{p = 10\%}$)

Figure 2-6 presents the sensitivity of expected ADAB program volume (y-axis) as the standard deviation of equivalent design premium (x-axis) is allowed to vary. A similar analysis is depicted in Figure 2-7. In both figures, the variable of interest was changed by keeping the remaining baseline variables constant. The decreasing ADAB probabilities with changing equivalent design premiums further highlight the need for agencies to calibrate their ADAB thresholds to maintain their target program volumes.

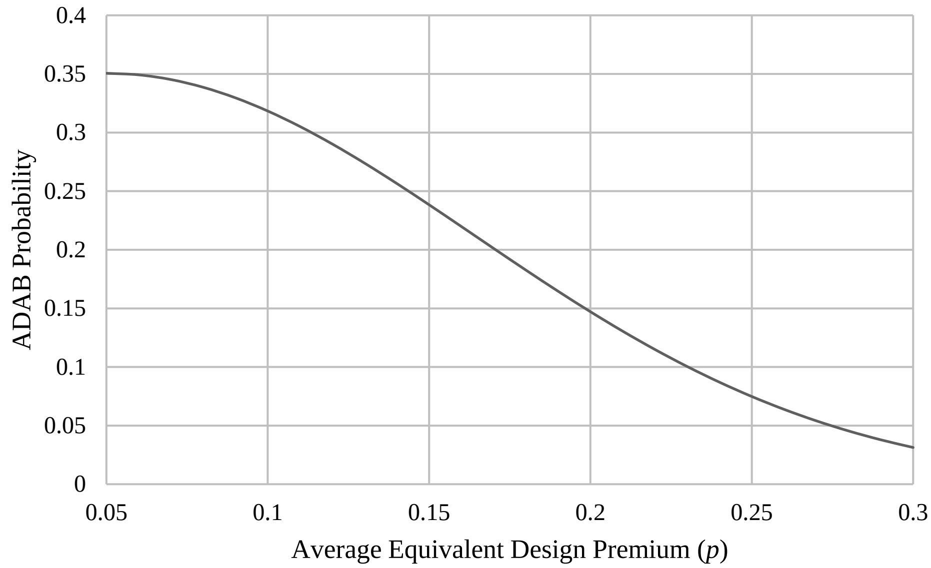

Figure 2-7 Sensitivity of ADAB probability to expected premium ($\boldsymbol{T = 10\%}$; $\boldsymbol{\sigma_p = 11\%}$)

Conclusions

The paper's analysis provides a succinct framework for studying the underlying factors that drive the size of agency ADAB programs. Its output argues that the current guidance for setting ADAB threshold criteria to screen candidate projects in pavement type selection decisions could be overly simplistic. Instead, the paper proposes an alternative perspective for modeling the uncertainty in equivalent pavement design costs. The paper's primary finding is to prove that ADAB threshold criteria should be a function of the variability in equivalent design premiums. As the expected equivalent design premiums increase/decrease, the findings suggest a corresponding change in agency threshold levels to maintain the target volumes of ADAB programs.

When agencies select qualifying projects for ADAB based on a life-cycle cost comparison among the alternates, the specified threshold level becomes the only lever for the agencies to influence the desired outcomes of an ADAB program. Once the decision to proceed with ADAB has been made, the sole remaining relevant factor becomes the alternative pavement type premium. In modeling the equivalent design costs for competing pavement type alternatives, the above analysis assumes the alternative premium as a random variable that inflates the baseline pavement design cost. The premium aggregates two major sources of uncertainty in the calculation of LCCs. First, the volatility of major construction material costs under different alternative designs precludes a deterministic estimation of design alternatives. Secondly, the wide range of LCC analysis assumptions, including those for the discount rate, salvage value, maintenance and rehabilitation strategies and the service period of different pavement type alternatives, makes the calculation of LCCs sensitive to the analyst's assumptions. Therefore, modeling such uncertainty in the form of a random variable for equivalent design premiums not only provides a reasonably realistic representation of the complex relationship between the equivalent design alternatives, it vastly simplifies the complexity of the analysis. The results indeed show that valuable insights can be gained in assisting agencies to make rational decisions on their ADAB threshold criteria.

Rather than setting a threshold level that remains constant as the spread between alternatives contracts or expands, the analysis shows, a dynamic threshold rate that takes into account input price volatility and future LCCs, can be used successfully, making the threshold levels relative to the alternative design premiums.

When selecting LCC thresholds, there is a direct relationship between the expected number of bids to be awarded through alternate bidding, and the potential project cost ranges for each alternative pavement type. Setting higher threshold levels results in a higher number of projects qualifying for alternate bidding. Conversely, low LCC thresholds reduce the number of projects that could potentially benefit from procurement using ADAB methods. Given the administrative and engineering bid costs associated with additional pavement designs, each agency can then balance the expected ADAB benefits, such as receiving market prices for competing alternatives, increasing competition, and reducing costs, against the costs of adopting ADAB practices.

The preceding discussion also provides the starting point in calculating the expected benefits of an agency’s ADAB program. Clearly, achieving an agency’s target ADAB program size is an exercise that should be tailored to each agency’s unique requirements and market conditions. However, since any such analysis must start from an estimation of the share of the agency projects that would qualify for alternate bidding, the proposed analysis can be used as a basis to both quantify and compare the anticipated costs and benefits of an ADAB program. Finally, in addition to laying the groundwork for future research in this area, this paper offers highly relevant insights for transportation agencies and administrators of public contracts.

CHAPTER 3. MODELING AIRPORT BUSINESS RISKS AND VALUATION OF FLEXIBILITY OPTIONS IN AIRPORT EXPANSION PROJECTS

A paper to be submitted to the *Transportation Research Record*, Journal of the Transportation Research Board of the National Academies of Sciences.

Karaca, I[1]; Savolainen, P.T[2]., Jeong, H.D[3].

Introduction

Airport investments are subject to considerable uncertainty in airport activity volumes. Although most airport investments are preceded by extensive forecasting studies, demand predictions can be highly inaccurate (Spitz and Golaszewski 2007; Kincaid et al. 2012, Flyvbjerg and Holm 2005). The long investment horizons of capital improvement plans often yield unmanageably large confidence intervals, and expected activity levels can quickly become the only factor that dominates valuation practices. Even though point estimates are almost always wrong (see the actual vs. realized demand levels for US airports in Figure A1 in the appendix), paradoxically, they can dominate investment decisions.

Compounding the high uncertainty in activity levels are the substantial size and irreversibility of such investments. Given the sizeable uncertainties in future demand forecasts (Transportation Research Circular E-C040), and the material opportunity costs associated with overinvestment, flexibility in planning airports becomes paramount. Premature investments and

[1] Corresponding author. Ph.D. candidate. Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 50011. E-mail: ikaraca@iastate.edu

[2] Associate Professor of Civil Engineering, Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 5001. E-mail: pts@iastate.edu

[3] Associate Professor of Civil Engineering, Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 5001. E-mail: djeong@iastate.edu

non-optimal airport sizes can burden operators for years to come. Increased levels of leverage initially could even lead to higher borrowing costs due to the escalation of business risks.

As de Neufville and Scholtes (2011) emphasize "A flexible design permits but does not require expansion." Rigid investment outlooks can not only lead to underutilized airport capacity, but the lack of land and easement for future growth opportunities can also have substantial implications for airports' commercial viability under competition from regional rivals (de Neufville 2006). If forecast errors are expected to be sizeable then, such variations from the mean can be consequential for the operators and cannot be ignored. Conversely, overly optimistic outlooks on future activity levels can also lead to excess capacity, which may not be altered for the evolving future needs of the industry. Fortunately for airport operators, however, airport capital investment programs may furnish the ability to time expansion investments and to allow for engineering designs flexible enough to adapt to changing needs (see de Neufville and Wang (2006) for an example of how options "in" projects can be recognized). It should also be noted that a real options valuation methodology, such as the one followed here, is most applicable when the firm exerts monopoly-like control over the market (McDonald 1998; Damodaran 2005).

Thus, the purpose of this paper is to provide a modeling framework that draws attention to a central capacity and revenue trade-off present in airport expansion projects. The proposed simulation model reflects many of the practical challenges faced by airport operators in their efforts to value their expansion options. As Horonjeff et al. (2010) point out, in the aftermath of the September 11, 2001, terror attacks, and the wave of consolidation and mergers activity following the 2008 recession, airport planning processes have become increasingly cognizant of rare events and their effect on demand forecasts. The proposed simulation model here reflects these types of practical challenges faced by airport operators in their efforts to value their expansion options (see Caves and Gosling (1999), for instance, for cases on how investment phasing can be incorporated in long-term airport planning practices). In particular, the paper illustrates how two components of a flexible investment approach (flexibility in investment timing, and flexibility in engineering design) can create option values. In so doing, the paper provides an example of Monte Carlo simulation and bases expansion decisions on a flexible strategy that responds to future demand paths as future activity levels are revealed within the model's volatility assumptions. Expansion decisions try to strike a balance between creating the capacity to serve the anticipated demand volumes and deferring expansion until the demand patterns are well established. The proposed two-year expansion rule is an example of such decision making. In addition to this flexible investment decision rule, a second flexibility option—flexibility in design choices—is modeled to allow airports to recover lost activity. This mechanism, however, is only allowed when the airport has the flexibility to convert existing facilities into alternative uses necessary to accommodate new types of demand.

Airport expansion projects arguably lead to two broad types of opportunity costs. First, expansion projects, in essence, increase the operating leverage of the airport by adding relatively certain fixed costs in return for uncertain upside potential. Aggressive expansion strategies can place unnecessary burdens on airport operators by introducing risks for unutilized capacity levels, which, in turn, adds to the airports' operating leverages, and eventually to their business risks (for a discussion on the effect of operating leverage on financial asset returns see Novy-Marx (2011); Carlson et al. (2004)). Increased levels of business, in turn, is expected to increase the financing costs of capital investment programs (Bernardo et al. 2012).

Second, lost demand due to capacity constraints erodes potential upside benefits. Since these opportunity costs are not readily observable, they are ignored in this analysis. So are other types of important types of uncertainties, such as construction costs, and pricing risk (e.g., as Reynolds et al. (2013) point out, for instance, airport managers can have considerable leeway in raising rates to counterbalance rising demand at busy airports).

The first type of losses, on the other hand, can be quite substantial. The paper proposes a proxy measure for capacity utilization by normalizing current capacity levels by the historical maximum service levels. Since it is not possible to quantify lost upside traffic directly, this analysis focuses on downside risks. The lessons learned here could also apply to upside opportunities (e.g., increased operating leverage could imply a rapid growth in profitability for medium size airports, whose operating leverage is expected to be higher than larger and smaller airports due to their relatively active expansion programs).

The results of the simulation example show that flexibility in both cases can create additional value that would be overlooked in a static planning approach. Since the goal of the paper is to offer a valuation model that encapsulates the volatility implied by different components of the demand generating process, a significant portion of the discussion is dedicated to the modeling of shocks to airport activity levels (e.g., arrival and departure of hub airlines). The model captures an essential tradeoff in airport expansion projects: while expansion projects may expose the airport to higher downside risks if a hub airline leaves, they could also create the excess capacity to accommodate new hub activity. Since mean reversion, when present, acts as a systemic dampening mechanism that curbs potential excess capacity losses for an airport (which also reduces potential option values), a random walk process is assumed.

The paper also provides, based on Federal Aviation Administration (FAA) data, the initial analysis of the volatility in enplanement growth experienced by the largest 140 US airports for the 26-year period from 1990 to 2016 (FAA TAF 2016). Although the analysis of this volatility is in and of itself worth studying, its treatment is left for Chapter 4. In fact, as Chapter 4 should make it clear, not all airports are equally exposed to sustained drops in demand, and hence the proposed model is expected to be more relevant for airports that do not show evidence of mean reversion.

For the purposes of this study, when referenced, expansion projects relate to incremental airport capacity increases (Horonjeff et al. 2010; Reynolds et al. 2013), which may be modular in design. The addition of new terminal gates are examples of such projects, for instance. Although the results of the model would still be expected to apply to other capital improvement projects, such as the addition of runways, several components of the expansion model considered here would need to be altered to fully reflect the distinct investment and capacity features of such projects.

Finally, even though airport expansion projects make up the focus of the present discussion, the proposed valuation methodology and the results of the simulation model need not be confined to airport projects. In fact, similar dynamics—long investment horizons and considerable uncertainty over future demand and project costs—may afflict many infrastructure projects. The difficulty of forecasting tollway traffic is a well-known problem (Bain 2009).

The rest of the paper is organized into two main sections. Part I provides a brief overview of the simulation approach used here, which is followed by the initial analysis of the enplanement growth volatility, discussion of the drivers of flexible airport expansion strategies, and the presentation of the proposed simulation model. It introduces the simulation framework and model parameters that make up the model. Since the volatility of airport activity demand is expected to be the main driver of option value, a comparative analysis of enplanement growth by size for major US airports is also provided. As mentioned earlier, the two main areas of interest for the model are the value added to expansion projects through flexibility in investment timing and engineering design. The mechanisms through which these components are incorporated in the model are also explained. The results section presents the main findings of the simulation analysis and provides a discussion on the implications of the results for airport capital investment programs.

Part II offers the simulation results for a hypothetical expansion project, which provides support for the presence of incremental value added through adopting flexible design approaches for projects with irreversible investments and sizeable volatility over future demand levels.

Part I

Methodology

As mentioned previously, the unpredictability of airport activity levels is the primary factor that creates option values in the valuation of airport capital investment programs. As the FAA advisory circular on airport master plans puts it “passenger levels are of particular importance since they determine the size of the terminal building and other essential elements of airport infrastructure such as parking facilities and access roads” (FAA 2005).

There is a considerable body of work that applied Monte Carlo simulations in valuing real options (see Mun (2006) and the references and examples therein for several examples of Monte Carlo simulations). Airport capital investment projects, and in particular, the role of uncertainty on flexible design has also been an active research area (de Neufville 2008; Reynolds et al. 2013; Caves and Gosling 1999; Horonjeff et al. 2010; Odoni and de Neufville 1992;

Kincaid et al. 2012; Chambers 2007). This chapter follows the four-step methodology proposed by De Neufville and Scholtes (2011) as described below:

1. *Step 1.* Recognize the uncertainties in the project. Passenger enplanements are used as the main driver of uncertainty in this model.
2. *Step 2.* Identify the types of flexibility that are the most suitable for the uncertainties recognized in step 1. In an expansion project, these are designated as the flexibility in size, timing, and function.
3. *Step 3.* Choose the optimal flexible design strategy and incorporate into the design. This step is executed through a Monte Carlo simulation model, which generates a probability distribution function for the NPV of the expansion project. A special emphasis is also placed in tracking the excess capacity distributions separately.
4. *Step 4.* Plan for the implementation of the flexible design strategies by monitoring the conditions deemed suitable to exercise flexibility options. Monitor and adapt flexible design strategies as needed. Since this step involves continuous monitoring of investment strategies and necessary adjustments as needed, it is not included in what follows.

Step 1. Volatility in Airport Activity Levels

This section discusses the relationship between airport size and historical enplanement volatility for US airports. Analyzing changes in enplaned passenger over time is an important step to verify the validity of probability distributions for the inputs used to generate the target function through the Monte Carlo simulation analysis. Table 3-1 provides the summary statistics for both the enplanement levels and yearly percent change series. The analysis provided here is entirely based on the yearly changes in enplanement growth rates.

Table 3-1. Summary statistics of passenger enplanement data by airport size

	Large	Medium	Small	All
Yearly passenger enplanements				
Mean	15,508,816	3,945,670	775,726	4,624,918
Median	13,853,299	3,581,177	612,518	1,529,334
Max	50,120,617	15,395,308	3,311,931	50,120,617
Min	1,980,046	1,030,627	117	117
Std. Dev.	8,150,153	1,966,017	487,669	6,917,821
Skewness	1.34	2.11	1.08	2.54
Kurtosis	4.88	9.77	4.01	10.48
Observations	783	918	2052	3753
Yearly change in enplanements				
Mean	0.0259	0.0161	0.0220	0.0214
Median	0.0264	0.0201	0.0111	0.0177
Max	0.3793	0.7552	1.6794	1.6794
Min	-0.2865	-0.4382	-0.4571	-0.4571
Std. Dev.	0.0621	0.0836	0.1225	0.1035
Skewness	0.2986	0.5894	3.2268	3.0037
Kurtosis	7.2618	14.4378	31.3139	35.2390
Observations	750	884	1,956	3,590

While enplanement volumes seem to be indistinguishable among airports of different sizes at first glance (Figure 3-1), upon closer inspection, a different pattern emerges when the variation enplanement volatility is examined within the three groups (Figure 2). This step is also used to set a reasonable range of growth rate and variance assumptions as inputs to the Monte Carlo simulation exercise.

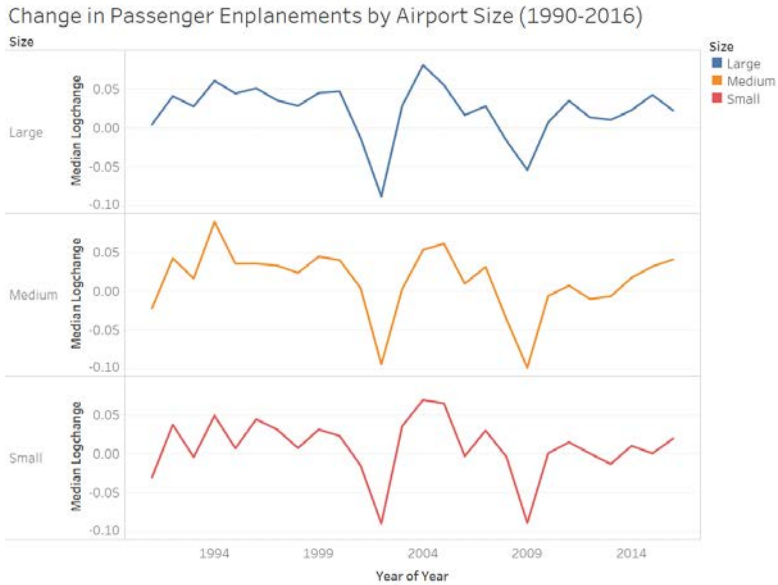

Figure 3-1 Change in passenger enplanement by airport size from 1990 to 2016

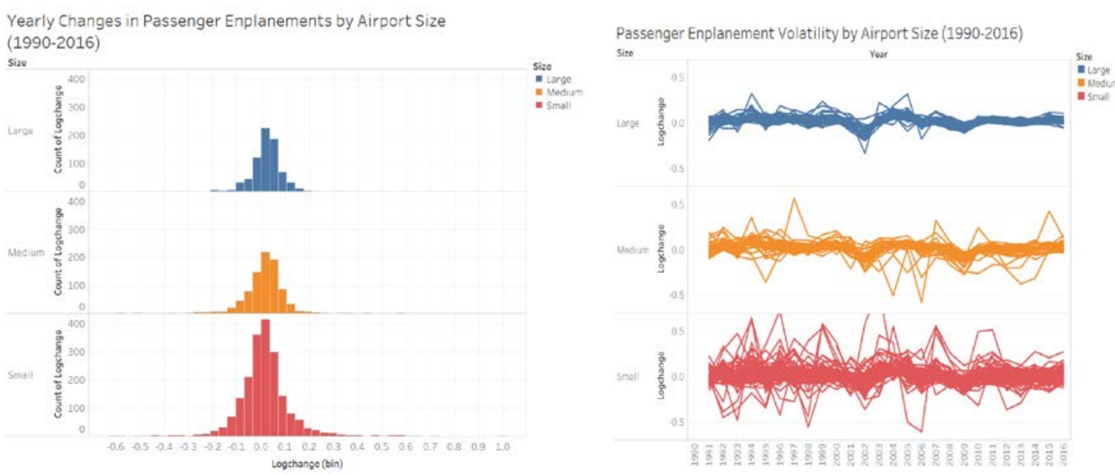

Figure 3-2 Distribution of changes in passenger enplanement by airport size

To determine whether the three size categories were statistically different from one another, the study conducted equality tests for mean, median, and variances (Table 3-2). As evidenced by the six statistical test results shown in Table 3, the three airport size categories have unequal means, medians, and variances at practically any significance level.

Table 3-2 Summary of equality tests for changes in enplanements by airport size

Method	df	Test statistic	Probability
Test for equality of means			
Welch F-test	(2, 2086)	3.7177	0.0245
Test for equality of medians			
Med. Chi-square	2	37.9716	0.0000
Kruskal-Wallis	2	25.9264	0.0000
Test for equality of variances			
Bartlett	2	479.3247	0.0000
Levene	(2, 3587)	42.9518	0.0000
Brown-Forsythe	(2, 3587)	40.0354	0.0000

Step 2. Identifying the Nature of Flexibility

How flexibility in planning and phasing of airport capital investment projects have been extensively documented (De Neufville 1995; 1995a; 1995b; 2008; Chambers 2007; Burghouwt 2007; Gosling 1999). In particular, see the overview, references, and cases provided by Chambers (2007). Although many factors contribute to the eventual implementation of capital improvement projects (Horonjeff et al. 2010; de Neufville and Odoni 2013; Kincaid et al. 2012), the risks that contribute to the revenue generating potential of expansion projects may include risks related to traffic volume, such as the relative size of expansion, carrier concentration and share of O&D enplanements, and the risks associated with airport user pricing and fees, including airline use and lease agreements, cost per enplanement (CPE) rates, and competition from other airports.

Airport expansion projects, in essence, increase the operating leverage of the airport by adding relatively certain fixed costs in return for uncertain upside potential. As such, airport operators may weigh the opportunity costs of waiting against deferring expansion decisions until growth patterns in demand are well established. The model’s two-year expansion rule is an example of such decision making. The two types of flexibility options are identified as follows.

Flexibility in timing: Instead of a now-or-never investment decision implied in static NPV decision rules, a dynamic investment approach that responds to changes in demand is adaptive to maintaining existing capacity levels when the expected growth in activity levels do not materialize. In the proposed valuation framework, airport capacity is added incrementally only after a threshold that signals the quality of the growth trends is breached (e.g., two consecutive years of unfulfilled demand triggers expansion decisions).

Flexibility in engineering design: An airport's capability to adapt to the shifting functional requirements of the aviation industry, such as the evolving security considerations and terminal design guidelines (Odoni and de Neufville 1992; de Neufville et al. 2002), secures the flexibility to accommodate future positive jumps when they arrive. The lack of ability to adjust to new functional requirements would arguably restrain the fulfillment of new demand on airport facilities. This dynamic is captured by permitting the arrival of positive jumps only when flexibility options to reconfigure excess airport capacity for new functional uses are present. This feature acts as insurance against losses when negative jumps occur. When a hub airline leaves an airport, excess capacity left behind can be filled by other airlines, or even can lead to a different composition of air traffic.

Table 3-3 Main drivers of business risk in airport expansion projects

	Low Carrier Concentration & Low Connecting Enplanements	**High Carrier Concentration & High Connecting Enplanements**
Incremental expansion projects to keep up with growing demand	Lower downside risks Common in larger airports	Medium risk Common in medium/small airports
Major expansion projects with excess capacity in the short term	Medium risk Common in medium airports	Higher downside risks Common in medium/small airports

Due to the highly unpredictable nature of business risks faced by airport operators (summarized in Table 3-3), the arrival of jumps in demand is assumed to follow a Poisson process as defined more fully in the presentation of the proposed model (see de Neufville and Sholtes (2011) on the use of exponential distribution in airport planning applications).

Modeling passenger enplanement data

Studying historical changes in the demand variable is a reasonable starting point in modeling the range of future uncertainties. Since the emphasis of the present paper is not on evaluating the relative forecast performance of alternative functional specifications, a geometric Brownian motion process is chosen as a reasonable demand generating function for the purposes of the paper. Without a doubt, the true nature of uncertainties can be further improved through more sophisticated forecasting methods (Bhadra and Schaufele, 2007). Rather than obtaining the best fitting model specification that could potentially lead to overfitting of the data, the emphasis is placed on identifying and characterizing the uncertainties that afflict the passenger enplanement volatility. As such, a particular focus is placed on modeling jumps and the concentration risk that contributes greatly to such shifts in demand. In addition to the geometric Brownian motion process that defines the baseline trend stationary process in enplanement growth, the two additional independent jump processes are discussed below.

Negative jumps

Dehubbing risks lead to considerably higher negative jumps compared to changes in origin and destination traffic, which are primarily driven by local economic conditions and business cycles. Consider the dramatic drops experienced by four medium size airports (Cleveland (CLE), Cincinnati (CVG), Pittsburg (PIT), and St Louis (STL)) in the past decade, for instance. All four airports suffered unusually large losses after losing their hub airlines whose connecting traffic accounted for the considerable portions of the airports' total activity levels. Negative jumps are, therefore, generated to reflect the concentration risk of airports' connecting traffic compositions. Thus, although the arrival of the negative jumps is modeled to follow a Poisson process, the magnitude of jumps is calibrated to account for the concentration risk of the airport. As it is argued in Chapter 4, if negative jumps for medium airports are indeed more persistent, the option value of flexible expansion designs becomes even more critical.

Positive jumps

Similarly, positive jumps are expected to occur following a Poisson process. Unlike negative jumps, however, positive jumps are capacity constrained, and, consequently, are expected to be downward biased. Stated differently, if there is no available capacity when positive jumps arrive, additional capacity requests are fulfilled to the extent that there is available airport capacity. Positive demand jumps also provide the mechanism through which the flexibility in airport design comes into play. An airport's capability to adapt to the shifting functional requirements of the aviation industry, such as the evolving security considerations and terminal design guidelines (Odoni and de Neufville 1992; de Neufville and Barros 2002), secures the flexibility to accommodate future positive jumps when they arrive.

A variant of this dynamic can also be included into the model if flexibility is desired to influence the retention of existing airport business. That is, lack of flexibility in airport design can accelerate negative jumps in demand. Thus, in further refinements of the model, the arrival of positive jumps can be calibrated to specific airport characteristics. In the present formulation, however, this dynamic can still be approximated by altering the rate parameter in the Poisson distribution. Further, because not all airports have the ability to influence their demand compositions due to various reasons (e.g., lack of available land, environmental, noise, and other considerations), possible extensions to the model could examine the effects of capping expansion sizes on option valuations.

Step 3. Evaluation of Competing Alternatives

This section identifies two alternative assessment methods in evaluating the relative performance of competing decision alternatives. The first of these two methods is the standard decision rule based on maximizing the project NPV, which itself is based on the standard discounted cash flow analysis. When project valuations follow a probabilistic distribution, not only the expected values but their variance becomes an important consideration. The goal then is to be able to move the NPV curve to the right as much as possible and limit the Value-at-Risk amounts.

Although the second decision evaluation measure, capacity utilization or, equivalently, excess capacity levels, is still closely related to the NPV distributions, it merits special attention on its own because it highlights the irreversibility capital investments and the potential downside risks imposed on airport operators, who are expected to experience higher operating leverage levels following expansion projects.

The proposed airport activity model

For tractability of the results, the proposed model includes two components: a geometric Brownian motion with drift and the Poisson distribution for jumps in demand. For the drift value, the FAA forecasts can be used (FAA Terminal Area Forecast 2016). The analysis of the enplanements data provided the majority of the insights that led to the demand specification presented in this section.

The specified model follows a random walk process, i.e., no mean reversion is at play (Figure 3-3 demonstrates potential demand paths (excluding jumps in demand). This modeling choice can be defended on two counts. First, mean reversion, when present, acts as a systemic dampening mechanism that curbs potential excess capacity losses and diminishes the potential option values that can be captured through flexible planning approaches. Second, a random walk process produces reasonably realistic demand paths for airports that experienced the largest drops in their activity levels. The persistence of such losses is the defining characteristic of random walks.

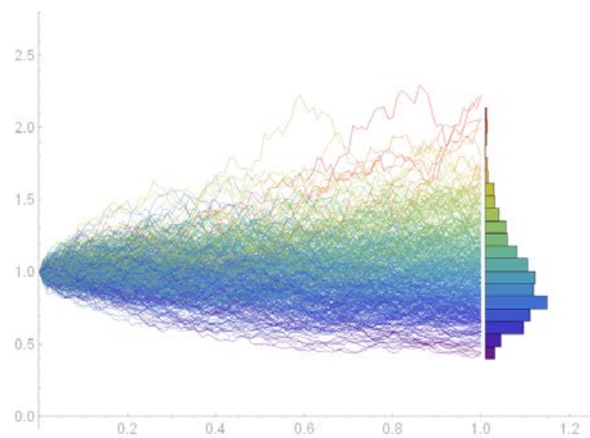

Figure 3-3 Simulation of airport activity paths over time

The model captures an essential tradeoff in airport expansion projects: while expansion projects may expose the airport to higher downside risks if a hub airline leaves, they could also create the excess capacity to accommodate growing demand levels, and even new hub activity if likely. Expansion projects are assumed to ease capacity constraints incrementally and are finished within a year. Passenger enplanements, at time t, (P_t), for a given airport is defined by Equation 3-1.

$$\boldsymbol{Number\ of\ enplaned\ passengers\ (P_t) = P_{t-1}\ \exp(\mu_p + \sigma_p W_t)} \qquad \textbf{Equation 3-1}$$

where μ_p is the drift term in passenger enplanements, while σ_p is the standard deviation of enplanement growth. The stochastic disturbance in enplanement volumes is represented with a Wiener process, $W_t \sim N(0{,}1)$.

Jumps in airport activity levels

Since both positive and negative jumps follow a Poisson process, the cumulative distribution function can be used to calculate the probability of an event occurring in one year. Positive jumps are defined separately under flexible and rigid design alternatives to account for the value of flexible design options in accommodating new arrivals of demand, e.g., through new hub airline activity.

If flexible design options that permit conversion between different functional requirements for airport capacity is present, Equation 3-2 provides the CDF of such events under the exponential distribution of the waiting times between their arrivals

$$\boldsymbol{CDF\ of\ positive\ jumps\ F(t;\lambda_{PJ})} = [\mathbf{1} - \mathbf{exp}(-\boldsymbol{\lambda_{PJ}t})] \qquad \textbf{Equation 3-2}$$

where λ_{PJ} is the rate parameter that captures the arrival frequency of positive jumps.

When no options for conversion of airport capacity is available, however, the probability of positive jumps occurring is zero ($CDF\ of\ positive\ jumps\ F(t;\lambda) = 0$). Equation 3-3 quantifies such jumps as

$$\boldsymbol{Positive\ jumps\ given\ jump\ occurs\ (PJ_t)} = \boldsymbol{P_{t-1}}[\mathbf{exp}(\boldsymbol{\mu_{PJ}} + \boldsymbol{\sigma_{PJ}W_t}) - \mathbf{1}] \qquad \textbf{Equation 3-3}$$

where μ_{PJ} is the mean surge in enplanements, and σ_{PJ} is the standard deviation of such spikes in demand.

In contrast, negative jumps are equally likely under both with and without flexible engineering design (Equation 3-4), and the magnitude of such drops is given by Equation 3-5.

$$\boldsymbol{CDF\ of\ negative\ jumps\ F(t; \lambda_{NJ})} = [\mathbf{1} - \mathbf{exp}(-\boldsymbol{\lambda_{NJ} t})] \quad \textbf{Equation 3-4}$$

where λ_{NJ} is the rate parameter that captures the arrival frequency of positive jumps.

$$\boldsymbol{Negative\ jumps\ given\ jump\ occurs\ (NJ_t)} = \boldsymbol{P_{t-1}}[\mathbf{exp}(\boldsymbol{\mu_{NJ}} + \boldsymbol{s\sigma_{NJ} W_t}) - \mathbf{1}] \quad \textbf{Equation 3-5}$$

where s is the scale parameter for concentration risk of connecting passenger enplanements, μ_{PJ} is the mean negative jump in enplanements, and σ_{PJ} is the standard deviation of such drops in demand.

Given the three components of the demand equation, the unconstrained enplanement demand can be written by Equation 3-6. Once the capacity constraints are imposed, the serviceable demand then can be defined by Equation 3-7.

$$\boldsymbol{Unconstrained\ enplanement\ demand\ (D_t)} = \boldsymbol{P_t} + \boldsymbol{PJ_t} + \boldsymbol{NJ_t} \quad \textbf{Equation 3-6}$$

$$\boldsymbol{Fulfilled\ enplanement\ demand\ (FD_t)} = \begin{cases} \boldsymbol{C_t} & \boldsymbol{if} \quad (\boldsymbol{D_t}) \geq \boldsymbol{C_t} \\ \boldsymbol{D_t} & \boldsymbol{if} \quad (\boldsymbol{D_t}) < \boldsymbol{C_t} \end{cases} \quad \textbf{Equation 3-7}$$

Concentration risk

The following two variables are expected to determine airports' business risks, and, thus, their exposure to downside risks, due to the concentration risks present in their connecting traffic compositions:

1. Origin and destination (O&D) vs. connecting traffic composition;
2. Airline concentration in connecting passenger enplanements.

$$\boldsymbol{No.\ of\ enp.\ (P_t)} = \boldsymbol{Origin\ \&\ Dest.Enp.(OD_t)} + \boldsymbol{Connecting\ Enp.(T_t)} \quad \textbf{Equation 3-8}$$

The scale parameter, s, for negative jumps can be thought as the concentration index for negative jumps, which is identical to the Herfindahl–Hirschman Index (HHI) in its construction (Equation 3-9). The HHI is a widely used tool in measuring the competitiveness of an industry by summing the squares of each firm's market share (see the references to the HHI in the Horizontal Merger Guidelines of the US Department of Justice). While higher values indicate a monopolistic market concentration, the existence of many competing firms leads to values close to zero. Note that origin and destination enplanements are excluded from the calculation since this type of demand is assumed to be stable and immune to airline composition at a particular airport.

$$\boldsymbol{Scale\ parameter\ for\ negative\ jumps\ (s)} = \sum_{i=1}^{n}\left(\frac{T_{it}}{T_t}\right)^2 \qquad \textbf{Equation 3-9}$$

Decision rule for expansion projects

Instead of making an expansion decision based on a static NPV analysis *ex-ante*, a dynamic investment decision, such as the one used here (Equation 3-10), triggers an investment project only when the total demand (D_t) exceeds capacity (C_t) for two years in a row:

$$\boldsymbol{Expansion\ (X_t)} = \begin{cases} \mathbf{1} & \boldsymbol{if\ D_{t-2} \geq C_{t-2} \cap\ D_{t-1} \geq C_{t-1}} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad \textbf{Equation 3-10}$$

Although there is no limit to alternative decision rules that can be used to trigger investments, the two-year rule provides a simple example of how such decision rules could work in practice. The current airport capacity can then be updated following the outcome of the expansion decision as in Equation 3-11.

$$\boldsymbol{Airport\ capacity\ (C_t)} = \boldsymbol{C_{t-1} + X_{t-1}\,\Delta C} \qquad \textbf{Equation 3-11}$$

Given the sizeable fixed costs and the irreversibility of the expansion investment, the two primary types of opportunity costs—excess capacity levels, and unfulfilled demand—are then defined by Equations 3-12 and 3-13, respectively.

$$\boldsymbol{Excess\ capacity\ (EC_t) = \begin{cases} C_t - D_t & if\ D_t < C_t \\ 0 & if\ D_t \geq C_t \end{cases}}$$ **Equation 3-12**

$$\boldsymbol{Unfulfilled\ demand\ (UD_t) = \begin{cases} D_t - C_t & if\ D_t \geq C_t \\ 0 & if\ D_t < C_t \end{cases}}$$ **Equation 3-13**

The incremental revenues due to expansion is defined by Equation 3-14, which multiplies incremental demand serviced ($FD_t - C_0$) by the cost per enplanement (CPE), which is the airport operator only revenue stream for each enplaned passenger charged to airlines.

$$\boldsymbol{Incremental\ expansion\ renenue\ (R_t) = \begin{cases} (FD_t - C_0)CPE & if\ \sum_{i=0}^{t} X_i \geq 1 \\ 0 & otherwise \end{cases}}$$ **Equation 3-14**

where cost per enplanement (CPE) revenues are assumed to be net of variable operating expenditures, and C_0 is the initial airport capacity.

Equation 3-15 defines the cost of each expansion phase which is given a constant of XC.

$$\boldsymbol{Expansion\ cost\ (XC_t) = \begin{cases} XC & if\ X_i \geq 1 \\ 0 & otherwise \end{cases}}$$ **Equation 3-15**

Finally, Equation 3-16 provides the annual cash flows necessary for the discounted cash flow calculations that result in the net present value of the expansion project (Equation 3-17).

$$\boldsymbol{Net\ cash\ flows\ attributable\ to\ expansion\ (XF_t) = (FD_t\ CPE) - C_0 - XC_t}$$ **Equation 3-16**

$$\boldsymbol{NPV\ of\ expansion = \sum_{i=0}^{n} \frac{XF_i}{r^i}}$$ **Equation 3-17**

where r is the discount factor given for the investment.

Model inputs

Table 4 provides the model inputs that were used to illustrate a hypothetical expansion project by using the enplanements demand equation introduced in Equation 3-16.

Table 3-4. Model Inputs

Existing capacity ('000)	1,100
Incremental expansion size ('000)	200
Default expansion size ('000)	1,300
Revenue per enplanement ($), CPE (net of variable operating costs, $/enplanement)	10
Demand variables	
Enplanements trend mean	0.02
Enplanements trend standard deviation	0.01
Positive jump mean	0.10
Positive jump standard deviation	0.05
Negative jump mean	0.20
Negative jump standard deviation	0.10
Expansion costs	
Initial expansion cost ($'000)	5,000
Expansion fixed costs / year ($'000)	100
Discount rate	0.05

Model outputs

This section presents the key outputs of the simulation model. Figure 3-4 shows that the results predict gradual capacity expansions as expected. Starting from an initial capacity of 1.1 million passengers, on average, the decision rule generates a single instance of expansion outcomes during the first five years of operations, which then reaches as high as three expansion decisions by year 10. Note that a dynamically adjusting expansion plan that adjusts to demand levels continually, as opposed to locking into a large capacity gradually over time. In the latter case, the project is still prone to substantial losses if the demand does not materialize.

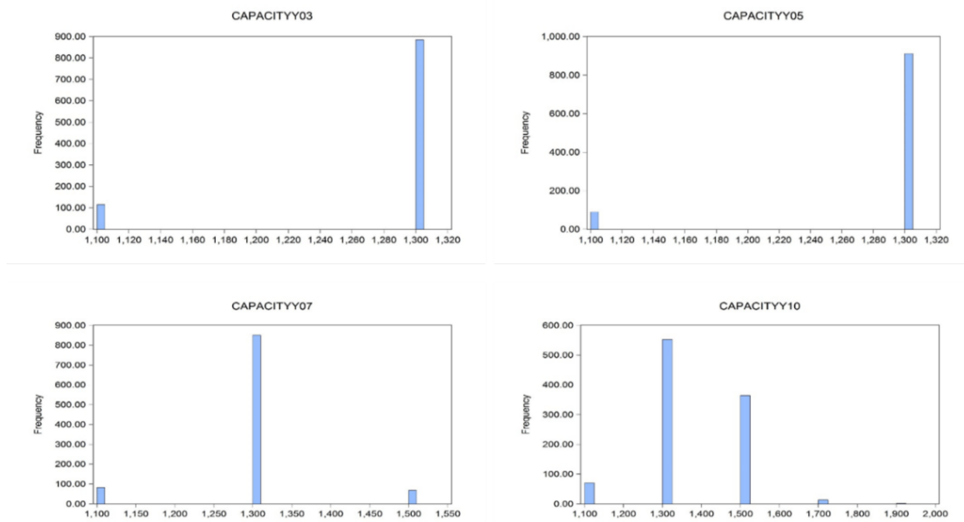

Figure 3-4 Progression of airport capacity over time (years 3, 5, 7 and 10 shown)

The gradual increase in capacity is, of course, expected given the trend stationary enplanement demand built into the model. Figure 3-5 illustrates the progression of the baseline demand distributions over time, which does not reflect the actual serviceable demand due to capacity constraints. As expected, the baseline enplanement demand reflects growing mean and variance due to the geometric growth in the series.

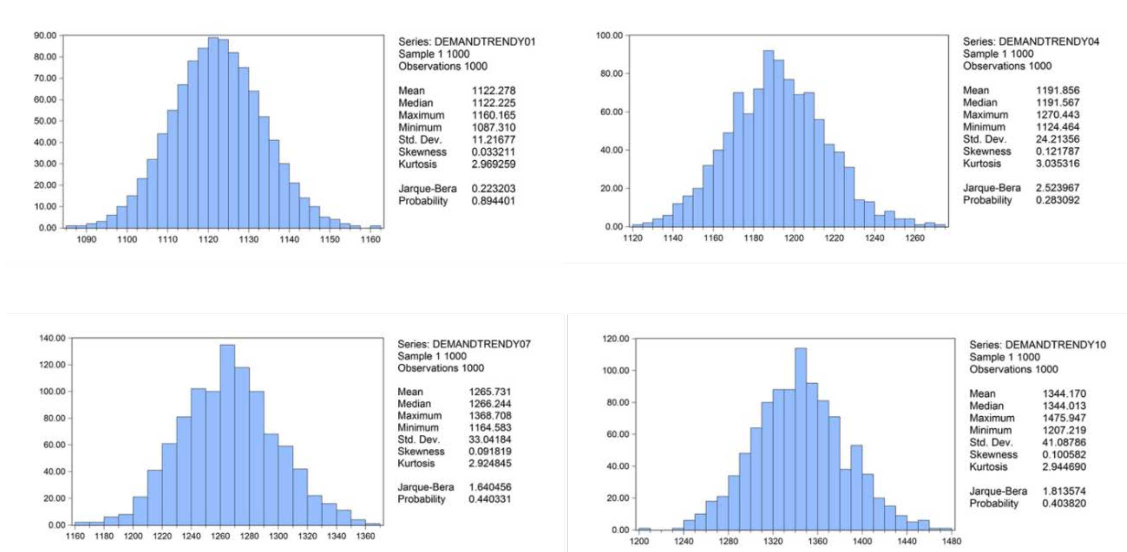

Figure 3-5 Progression of unconstrained enplanement demand, excluding jumps over time (years 1, 4, 7 and 10 shown)

Once both the negative and positive jumps in activity demand and the capacity constraints are factored in, however, the actual enplanement distributions are altered considerably (Figure 3-6). Significant negative skewness is present due to the presence of negative jumps, which is worsened by the elimination of upside potential due to capacity limitations. However, the presence of positive jumps dampens the effects of negative jumps by backfilling any available excess capacity, which, as stated previously, is the underlying mechanism for the degree of flexibility in airport design.

A lower optimal capacity for the expansion project under the dynamic approach should not come as a surprise because the static approach ignores the capacity constraint on the demand that can be fulfilled. The static NPV values are flawed because the severely skewed nature of project cash flows due to capacity constraints is ignored. Since expected NPV values are truncated at maximum capacity, the capacity restraints drive much of the uniqueness of results for the expansion project.

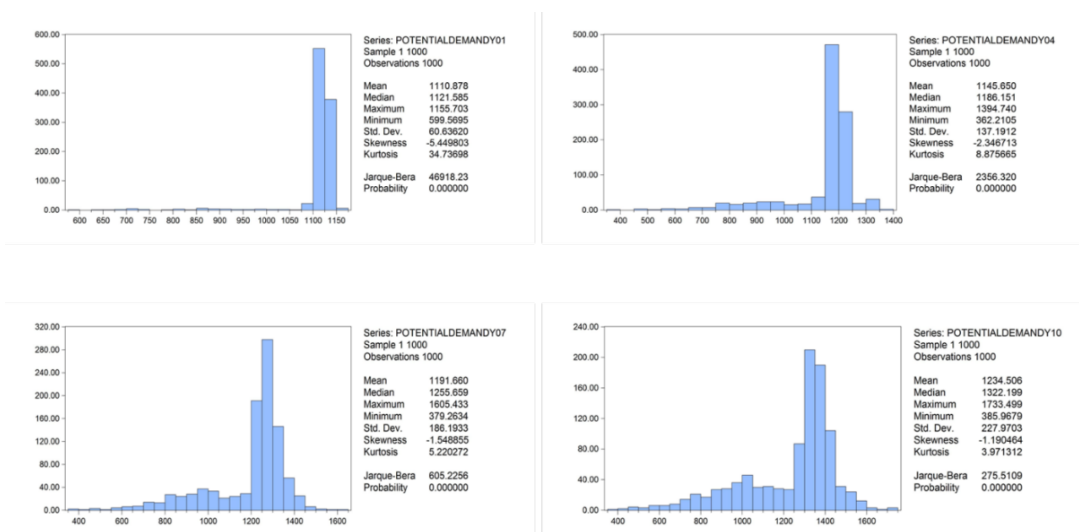

Figure 3-6 Progression of enplanement demand, including jumps over time (Years 1, 4, 7 and 10 shown)

The tradeoff between the incremental excess capacity exposure created by the expansion and the gains from previously unfulfilled demand is the main factor that determines the NPV and thus the economic viability of expansion decisions. Figure 3-7 shows how these opportunity costs, when expressed in excess capacity (top row) and unfulfilled demand (bottom row) vary over time.

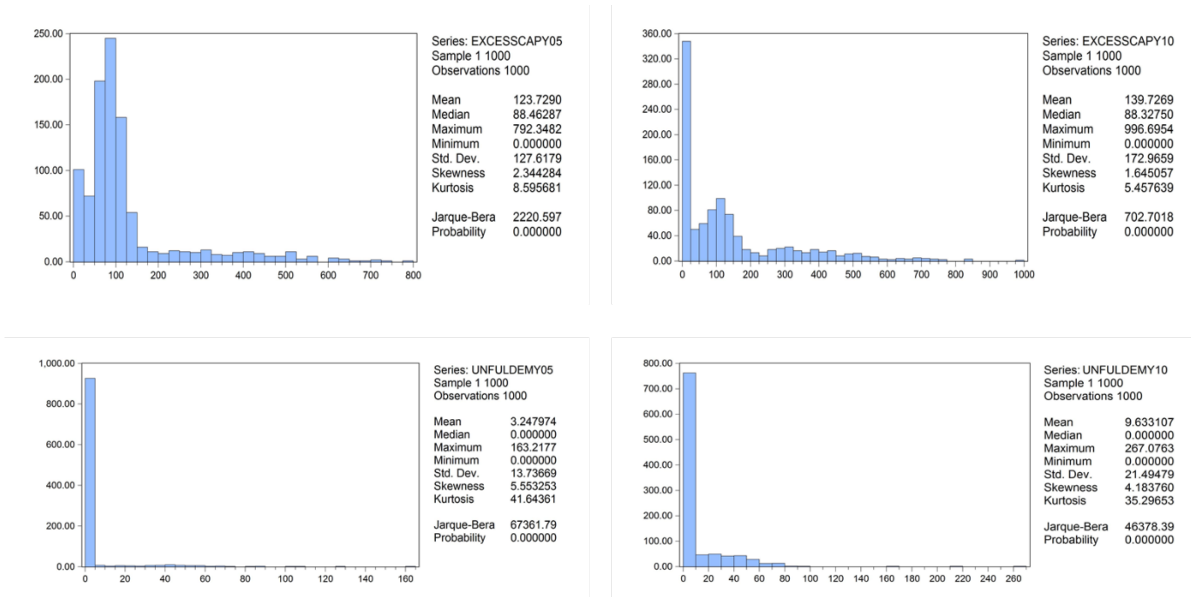

Figure 3-7 Tradeoff between excess capacity and unfilled demand over time (Years 5 and 10 shown)

Since excess capacity is identified as a critical performance parameter for the comparison of alternative expansion decision rules, Figure 3-8 and 3-9 further provide a comparison of excess capacity under two alternative—outright and flexible—expansion strategies. Figure 3-8 presents the difference in capacity utilization levels when a flexible expansion strategy is used. The ability to adapt to shifting demand, thus, creates economic value added by increasing the airport's operating efficiency.

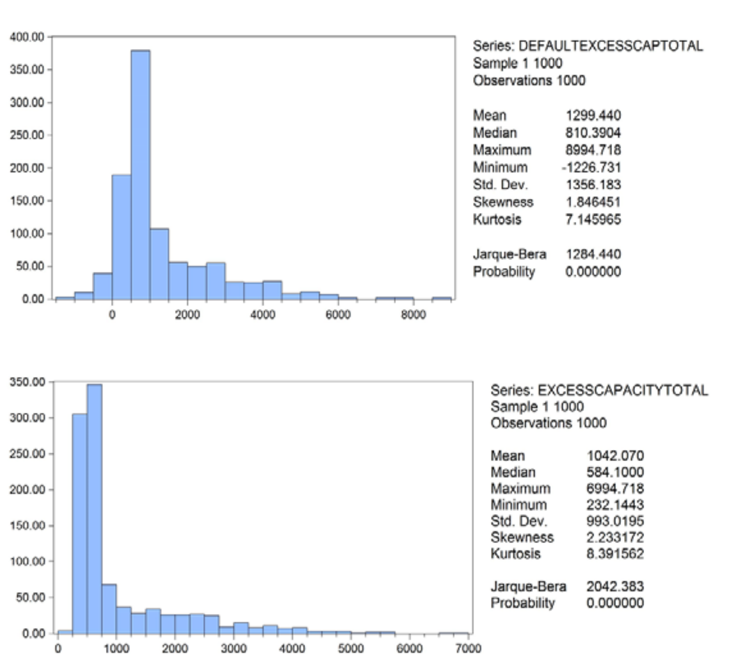

Figure 3-8 Comparison of excess capacity distributions between static and flexible investment rules

When comparing competing expansion strategies, in addition to comparing the excess capacity profiles under each expansion approach as a supplemental decision criterion, the option values can be directly calculated by differencing the net present values of the alternative expansion strategies.

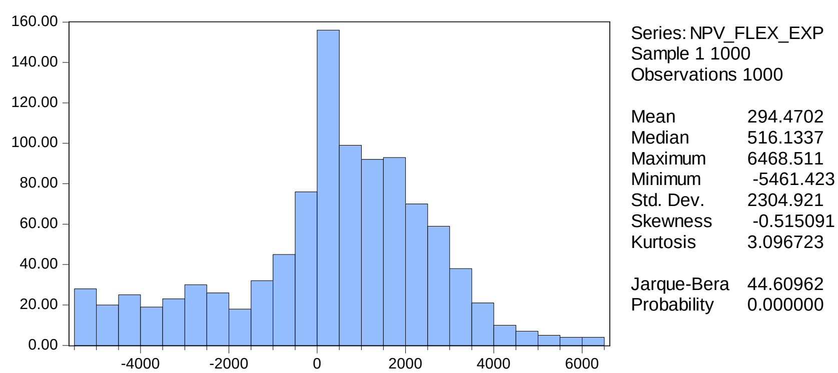

Figure 3-9 Incremental revenues from a flexible expansion approach

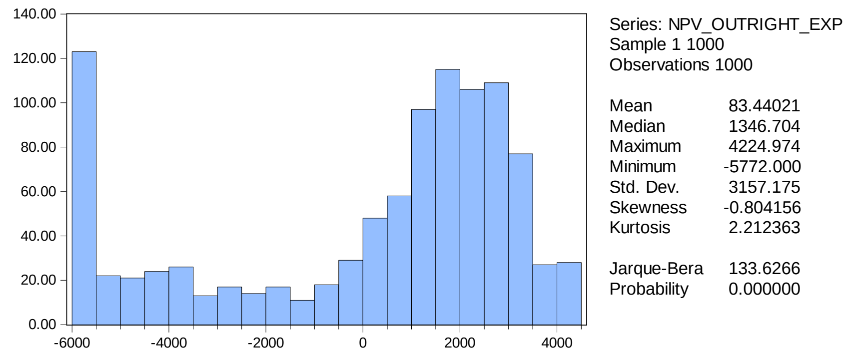

Figure 3-10 Incremental revenues from the outright expansion strategy

The comparison of the two alternative expansion approaches demonstrates how the flexible investment strategy can be expected to improve a rigid investment approach. First, note that the expected NPV for the flexible expansion ($294,470) is higher than the outright expansion approach ($83,440). Second, the flexibility in investment timing significantly reduces downside risks, by all but eliminating the clustering of the significant losses in the far left tail of the outright expansion strategy shown in Figure 3-11. Further, a flexible approach does extend the right tail of the distribution, compared to a rigid one, which results in capturing windfall revenues from sustained episodes of enplanement growth.

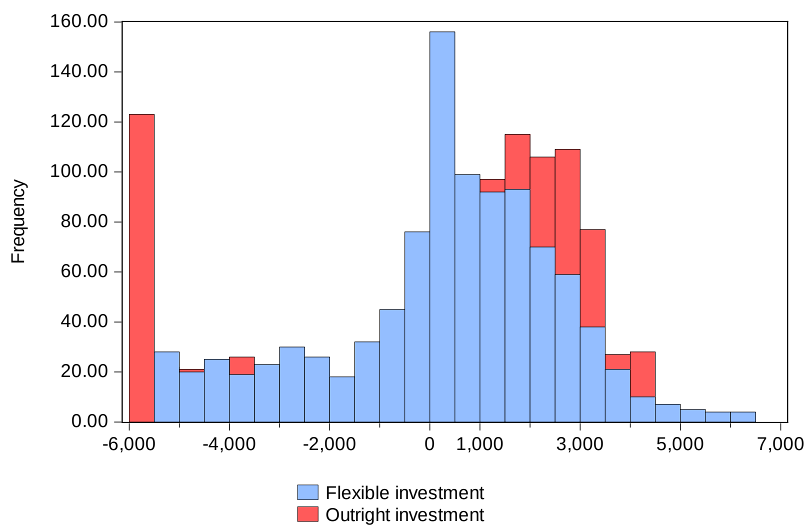

Figure 3-11 Superimposed NPV valuations for flexible and outright investment strategies

A standard method to compare how different alternative perform is to examine their cumulative distribution functions (CDF) as shown in Figure 3-12. In general, curves to the right represent improvements over the distributions to the left. Note that even so, there may not be a Pareto optimal investment strategy between all the alternative cases. Choosing more conservative expansion strategies lead to smaller potential losses, but may prove too cautious in capturing incremental revenues. However, outright yet overly optimistic strategies, in turn, may cause lower NPV amounts by capping the upside potential for revenue growth. The tradeoff is, thus, between the benefits of capping downside losses, the flexibility in adding incremental capacity as growth continues and the potential delay in expanding airport capacity timely in anticipation of future revenue growth.

As such, the flexible approach is not without its share of drawbacks. The particular investment rule chosen here proves to be too cautious in expanding capacity because the outright expansion strategy performs better in capturing enplanement revenues over a large share of the positive NPV range. This trade-off is, in fact, shown in Figure 3-12. The flexible expansion strategy offers improvements in the NPV profile by shifting the CDF curve to the right in the negative NPV range but falls short of doing so for the most of the positive range of valuations. Nevertheless, the flexible expansion strategy provides improvements over the rigid once again in the far positive valuations range, which is indicated by the position of the red line over the blue in the cumulative distribution function shown in Figure 3-12.

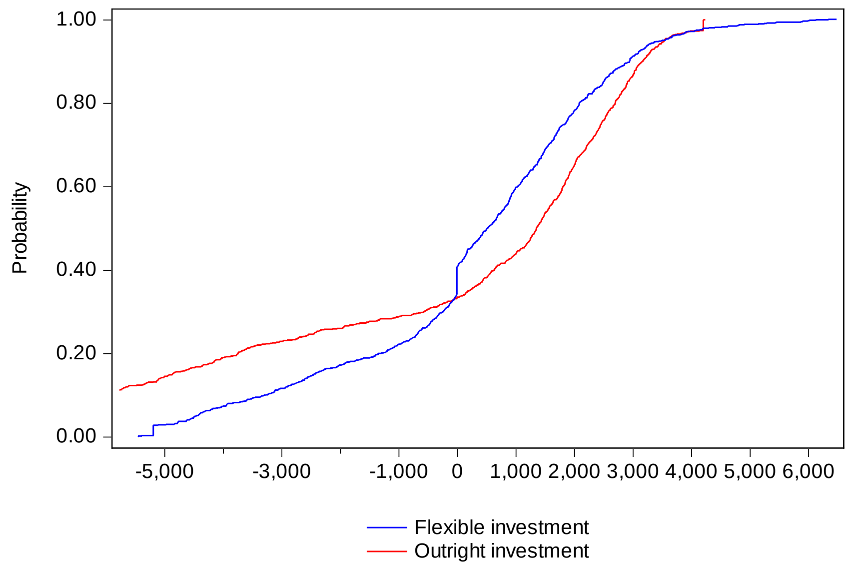

Figure 3-12 Cumulative density functions of project valuations under alternative expansion strategies

The value of the flexibility option in investment timing then can be obtained by differencing the project valuations under the two strategies shown in Figures 3-9 and 3-10. The resulting distribution, which is shown in Figure 3-13, is the valuation profile for the flexibility option in investment timing (note that both approaches include flexibility in design options, and no adjustment is necessary for this second type of option). The expected value of this highly asymmetrical distribution provides the option value in flexible investment timing as $211,030 in this particular example.

The value of the second type of option, flexibility in engineering design, can then be calculated by summing the net present value of the revenues due to positive jumps in demand. Figure 3-14 shows the NPV profile for this second type of option and produces an option value as $218,000 for the capability to accommodate new functional requirements for excess capacity.

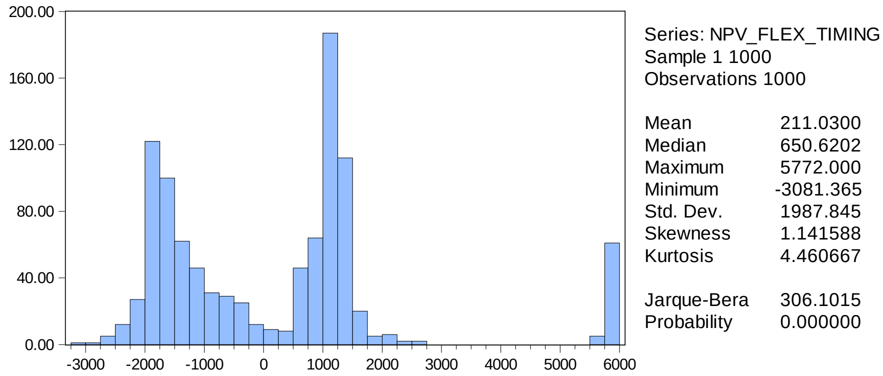

Figure 3-13 Option value for flexibility in investment timing

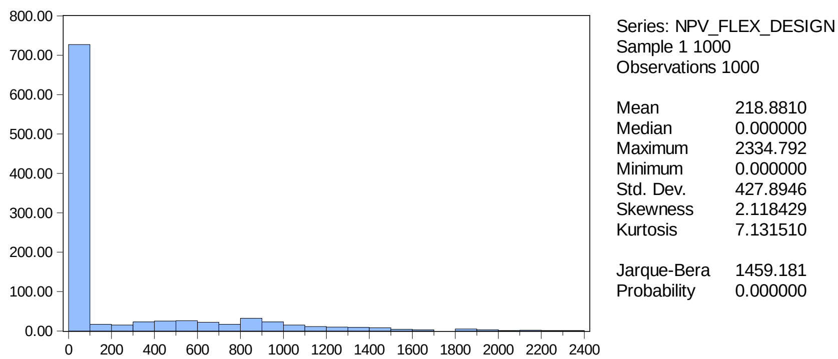

Figure 3-14 Option value for flexibility in engineering design

On balance, therefore, the results of the preceding analysis suggest that airport planners can add significant value from a real options-based valuation framework. Specifically, a dynamic approach that monitors and responds to trends in demand is shown to improve the risk profile of an expansion project. Simulation results confirm that a flexible expansion approach can provide improvements over outright expansion decisions by simultaneously capping downside exposure while positioning the airport to respond to sustained growth in enplanements through a series of incremental expansions.

The elimination of the extreme left-tail losses, in particular, corroborates the potential value of flexibility options in preventing those premature investments that are immediately followed by negative shocks in demand. Further, the airports' ability to convert excess capacity into new uses is expected to act as safety nets when activity levels fail to converge to their pre-shock levels and continue to accumulate.

Conclusions

Flexibility in investment timing and engineering design may create economic value that may otherwise not be captured in traditional NPV analyses. In fact, when investments cost are irreversible, the simulation analysis conducted here identified two mechanisms through which the presence of flexibility options could improve the operational efficiency of an airport's capital improvement program. First, a dynamic investment rule that monitors and responds to what are believed to be sustained trends in airport activity volumes introduces efficiencies by both capping downside losses and furnishing the flexibility for continued capacity increases. Second, the availability of flexible design options curtail excess capacity losses, *ex-post*, by attracting new business through adapting to the shifting needs of the industry.

The results of the simulation example also show that flexibility in both cases can create additional value that would be overlooked in a static planning approach. Since the goal of the paper is to offer a valuation model that captures the volatility implied by different components of airport activity demand, a large portion of the discussion is dedicated to the modeling positive and negative jumps observed in airport activity levels (e.g., arrival and departure of hub airlines). The proposed simulation model thus encapsulates an essential tradeoff in airport expansion projects: while expansion projects may expose the airport to higher downside risks if a hub airline leaves, they also create the capacity to service growing demand for air transport. The model further suggests flexible expansion strategies could provide considerable improvements over static NPV analyses. In fact, using a demand-based decision-making rule provides improved NPV profiles over an outright expansion decision. In aggregate, by improving airport's exposure to downside risks, flexible investment approaches could also lead to an increased level of investment activity for airports due to the addition of option values that would not be captured under rigid design strategies.

Although the benefits of flexible approaches in airport planning are widely reported, this study shows that option valuations should pay closer attention to the volatility of activity levels and both on a yearly and long-term basis. It shows, for instance, the valuation of flexibility options can be calibrated by a scale parameter that measures an airport's concentration risk in its connecting enplanement volumes. The paper expects the concentration risk to be at its highest when only a few airlines make up an airport's connecting traffic business and this volume represents a substantial share of overall airport activity. Unlike the origin and destination enplanements that are assumed to be relatively stable, losses in connecting traffic are assumed to exhibit no mean reversion properties.

The initial analysis of the enplanement data shows that large airports have not only outperformed medium and small airports in average growth rate, but they have also experienced lower variance levels in growth rates. Based on this evidence for the link between airport size and volatility in enplanement growth rates, as Chapter 4 will argue that medium sized hubs may stand to gain the most from an option-based valuation framework. The paper's findings further suggest that medium size airports may suffer from not only higher drops, but such drops may be more persistent when they arrive. Chapter 4 also demonstrates that the random-walk process assumption of the demand generating process utilized in the simulation model is most applicable to medium, and to a lesser extent, small size airports due to the lack of mean reversion in their capacity utilization levels over time.

Like all models, the proposed valuation model can be useful to the extent that simplification of reality is balanced with the reasonableness of its assumptions and their inherent logic. As such, the incremental expansion strategy tested here may not always be the preferred method of adding capacity. The advantages of outright expansion strategies (e.g., savings in construction costs due to economies of scale and disruption to airport operations) may often overwhelm any expected benefits from flexibility options. In addition, uncertainty in future financing costs may favor immediate construction of facilities.

Finally, having demonstrated how flexibilities embedded in expansion projects can be derived from the volatility of airport activity levels, this study is expected to both contribute to a fuller understanding of the underlying uncertainties that create option values, and add to the growing body of evidence for the relevance of flexible planning and design approaches for large engineering projects.

CHAPTER 4. VOLATILITY OF AIRPORT ACTIVITY LEVELS AND STATIONARITY OF CAPACITY USE FOR US AIRPORTS

A paper to be submitted to the *Journal of Transportation Engineering: Part A, Systems*, published by ASCE

Karaca, I[1], Cetin, K. S.[2]

Introduction

A better understanding of the changes in airport activity levels is crucial in the valuation of capital investment projects that often add considerable service capacity in anticipation of future activity volumes. Since such investments are justified on both the adequate and sustained nature of such future activity, and thus revenue, growth for airport operators, significant deviations from forecasts may lead to substantial losses. The recent experiences of several US airports that experienced rapid growth only to be faced with severe drops in their operations upon losing their hub airlines in the wake of the mergers and bankruptcies in the aviation industry exemplify the magnitude of risk associated with major expansion programs.

This paper seeks to examine the historical volatility recorded in passenger enplanements for the largest 140 US airports during the 26-year period from 1990 to 2016. The paper's findings suggest that despite the overall strong growth trend in total passenger enplanements, individual airport enplanement levels have shown extensive levels of volatility. In fact, when

[1] Corresponding author. Ph.D. candidate. Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 50011. E-mail: ikaraca@iastate.edu

[2] Assistant Professor of Civil Engineering, Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA 5001. E-mail: kcetin@iastate.edu

grouped as large, medium and small airports as per the FAA classifications by airport size, the volatility in enplanement growth varies considerably among the three groups.

Studying the changes in passenger enplanements is important for several reasons. First, it helps calibrate model input variables in valuing expansion options through Monte Carlo simulations. The simulation of the enplanement volumes should ideally include a drift component to account for the overall steady growth in air transport, and a second component to account for shocks, such as the arrival and departure of hub airlines, and lessening of capacity constraints. In building activity models, a time series analysis of activity levels can be especially informative to understand the effects of shocks over time, since different underlying processes necessitate different model specifications (Armstrong 2001). Of the many possible ways to simulate jumps in activity, as explained in Chapter 3, one possible approach is to model origin and destination and connecting passenger demand separately and assume that origin and destination demand is more stable relative to connecting enplanements. Further, concentration risk of airport operators to individual airlines can also be assumed to increase airports' enplanement volatility. Yet whatever the model specification may be, the challenge remains as to whether one can expect a recovery of potential losses in the long run.

The main finding of this chapter is that medium airports may be uniquely positioned to benefit the most from a flexible design approach. Not only do they seem to carry higher conditional Value-at-Risk levels, but these airports also have arguably more flexibility in converting excess capacity into new uses. The paper's analysis, therefore, suggests higher downside risks for medium hubs in the long run, i.e., persistent low capacity utilizations, despite the higher volatility of small hubs on a year-on-year basis.

A time series analysis approach to studying the airport capacity utilization levels would have the advantage of providing an abstraction from the necessity to account for complex explanatory variables to model airport activity levels. Instead, a time series approach searches for statistically significant patterns for autocorrelations and other time dependencies in the enplanements panel data. The ARIMA (Autoregressive Integrated Moving Average) time series model, as defined by Box and Jenkins (1970), provides the standard methodology for how this modeling approach can be applied in practice.

Since stationarity is the underlying assumption in modeling and analyzing time series data, unit root tests are often one of the first diagnostic tools employed before proceeding with further statistical analysis. The presence of a unit root in the series would suggest that effects of stochastic shocks are permanent and that the process is not mean-reverting.

The study is, thus, interested in investigating any evidence of stationarity in airport capacity utilization levels, in particular, because, if present, a stationary process would suggest constant mean and variance for the capacity utilization levels for a given airport over time. This property can then be used to build a hypothesis for the expected capacity utilization level for an airport in the long run. While a highly persistent series would suggest that jumps in enplanements tend to be permanent, lower levels of autocorrelations suggest jumps have relatively short-lived effects on enplanement levels. If true, this result is important because it provides a straightforward and valuable insight for the resilience of activity levels to negative shocks.

As a result, the stationarity of a series would imply that the capacity utilization levels would be mean-reverting, i.e., when the airport activity levels diverge from the long-term capacity utilization mean, say through a departure of a hub airline, the mean-reverting nature of the series would “pull back” the airport activity to the mean. In other words, if the observed capacity utilization level is above the mean, it would be expected to drop to the mean value, while downward deviations from the mean would result in subsequent upward adjustments toward the mean.

In approaching these questions, the paper assumes airport capacity utilization levels as a critical factor that ultimately determines the valuation of an expansion project. Thus, a large portion of what follows is dedicated to examining the effect of enplanement volatility on airport capacity utilization levels. Due to the emphasis placed on enplanement volumes, alternative delay-based capacity estimation metrics, such as annual service volume (ASV), and Aviation System Performance Metrics (ASPM) (FAA note 2004) were not applicable to the proposed model dynamics. Hence, airports’ capacity utilization levels are defined by their yearly enplanement levels normalized by the maximum individual enplanement levels previously recorded.

Having argued for the significance of persistent losses, the paper next turns to quantifying downside risks through a discussion of Value-at-Risk methods. The main finding of this section is that expansion projects are prone to considerable tail risks, and that airport revenues at risk can greatly increase if there is no evidence of mean reversion in airport activity levels. In light of this finding, despite their similar volatility levels, medium and small airports are expected to have considerably divergent values at risk due to the differences both in their average enplanement volumes, and the accumulation of potential losses. Similarly, while large airports have relatively low levels of volatility, they may also carry considerable Value-at-Risk levels due to their high volumes of average enplanements. Consequently, the airport operators’ *ability* to influence their demand composition and their relative need for flexible design and investment decisions may be, in fact, inversely related.

The paper is organized into three parts. The first part provides a discussion on the volatility of enplanement growth and airport size. The second is dedicated to the study of mean reversion. Finally, the third turns the paper's attention to Value-at-Risk and offers what is expected to be a conservative function to approximate capacity at risk levels for airports.

Airport size and volatility of passenger enplanements for US airports

Since a major driver of the flexibility in design options is an airport's ability to recover from negative shocks, this section provides the motivation for studying the persistence of capacity utilization levels more in detail in Part II.

In contrast to the modest and steady growth forecasts issued by the FAA for US passenger enplanements, which typically range from one to two and a half percent, airport activity levels are subject to substantial volatility and invariably differ from point estimates (Table 4-1). In fact, many airports have experienced sustained drops in their enplanement levels and have witnessed enplanement volumes below their 2015 volumes (included in the appendix). Figure 4-1 shows the geographical variation in enplanement volatility by airport size.

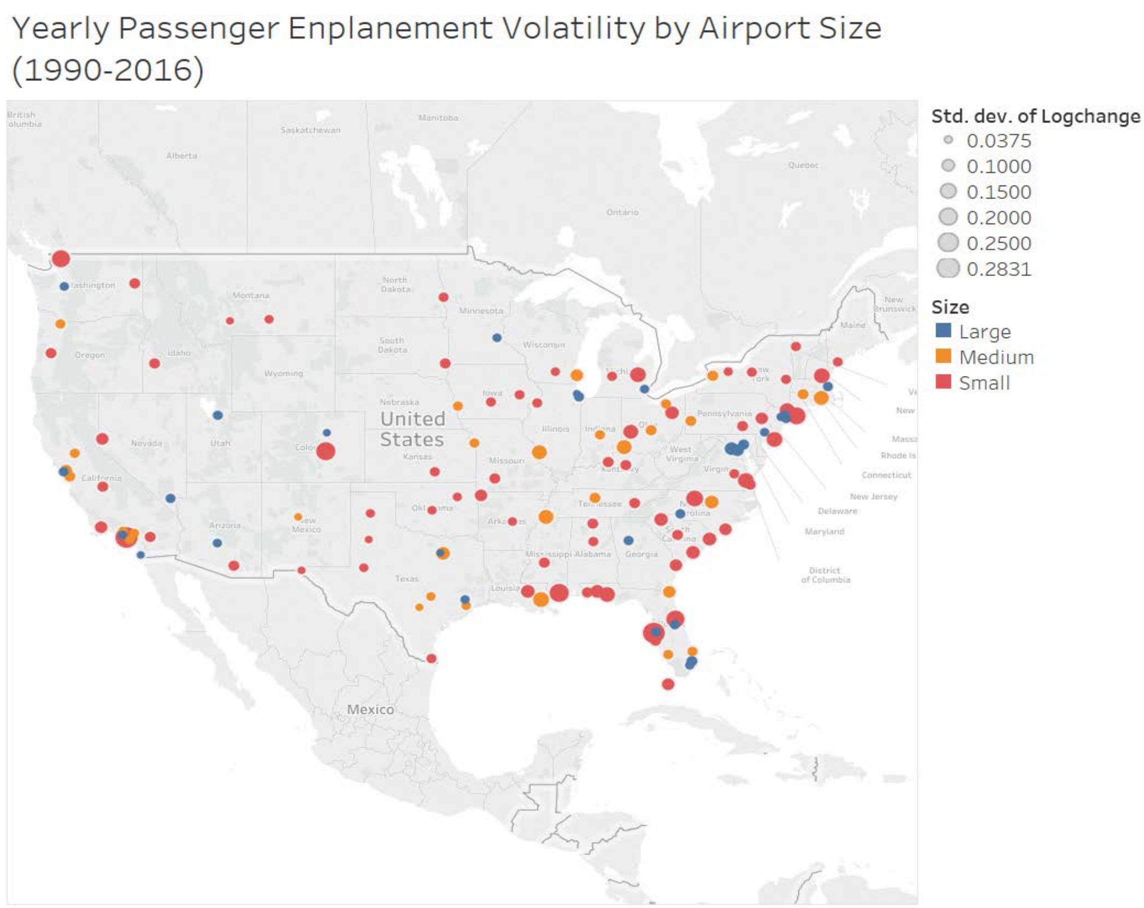

Figure 4-1 Yearly passenger enplanement volatility by airport size

Table 4-1 Forecast error of FAA passenger enplanements estimates (2010-2015)

Large	5 Year Forecast Error (%)	Medium	5 Year Forecast Error (%)
ATL	6.8	ABQ	31.8
BOS	-6.9	ANC	-12.8
BWI	11.9	AUS	-11.9
CLT	2.3	BDL	18.1
DCA	-12.0	BNA	-5.6
DEN	16.8	BUF	21.2
DFW	-0.4	BUR	15.4
DTW	16.0	CLE	36.4
EWR	2.7	CMH	14.0
FLL	4.0	CVG	50.9
HNL	-3.0	DAL	-28.3
IAD	37.1	HOU	-21.3
IAH	17.5	IND	7.5
JFK	2.3	JAX	21.2
LAS	6.2	MCI	10.1
LAX	-0.4	MKE	71.9
LGA	-11.0	MSY	-7.9
MCO	7.2	OAK	-10.6
MDW	-11.4	OGG	-12.2
MIA	-4.9	OMA	21.9
MSP	3.7	ONT	16.0
ORD	8.9	PBI	4.9
PDX	-1.2	PIT	15.4
PHL	19.7	RDU	16.9
PHX	-1.5	RSW	10.7
SAN	-2.8	SAT	10.4
SEA	-7.7	SJC	-4.8
SFO	-5.3	SJU	-2.5
SLC	7.4	SMF	3.7
TPA	8.4	SNA	-3.7
		STL	22.5
Mean	**3.7**	**Mean**	**9.7**

*Positive values indicate lower forecast levels than actual. Source: FAA APO Terminal Area Forecast 2015)

When the yearly enplanement volatility is examined, a clear pattern between enplanement growth rate volatility and airport size emerges (Figure 4-2). The standard deviation of enplanement growth rates is closely related to airport size, which suggests that option values are likely to be a function of airport size. By this line of reasoning, the option valuations for flexibility in expansion strategies should be the highest for small airports and lowest for large airports, all else held constant.

If the volatility of activity levels are stationary, however, limiting the valuation analysis on yearly volatilities alone would lead to misleading conclusions. Since the presence of mean reversion in capacity utilization levels, for instance, would imply that the effect of severe drops would tend to dissipate over time and the airport would converge its mean capacity utilization level in the long run, high growth rate volatility would not necessarily lead to high option valuations. Therefore, flexibility option valuations are expected to be the greatest especially for airports that follow a random walk process in their capacity utilization levels. As such, yearly volatility of growth rates and actual levels of enplanements can give very divergent results if the series for different airport sizes follow different time series processes.

Indeed, as the panel data analysis suggests, unlike the large and small size airports, which show evidence of mean reversion their capacity utilization levels, the medium size airports seem to follow a random walk process. The implication of this finding is that Value-at-Risk calculations based on yearly growth rates may overestimate actual capacity utilization levels for medium size airports if there is no evidence of mean reversion for such airports.

Second, volatility is only one input for the valuation of expansion options. The capacity at risk discussion that concludes the paper provides a tool to normalize the potential losses across airports of different sizes. When both average enplanement volumes and a range of historical changes in growth rates are taken into consideration to calculate potential losses, the relative importance of flexible planning options may be the highest for large airports due to their outsized enplanement volumes, despite their growth rate volatility being the lowest.

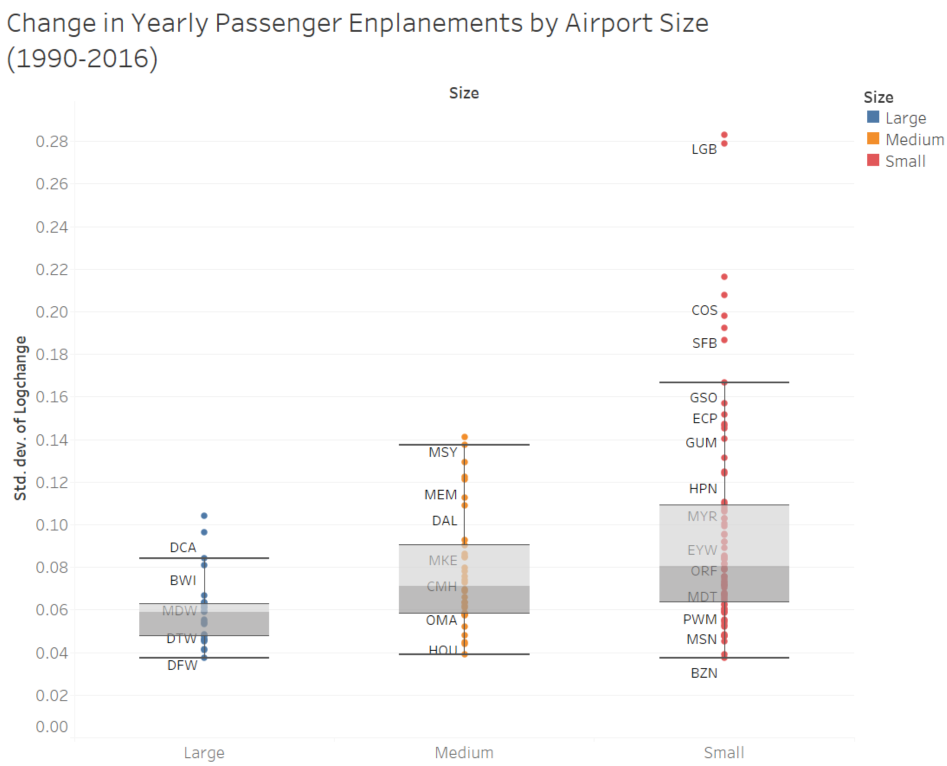

Figure 4-2 Volatility of enplanement growth rates by airport size

The next two graphs (Figures 4-3 and 4-4) indicate that the trajectories of the leading losses in medium and small airport categories may, indeed, be following different time series processes. Since major dehubbing events were the cause of the sharp drops illustrated in Figure 4-3, the persistence of losses, unlike those in small airports (Figure 4-4), suggests that volatility of yearly enplanement growth rates may lead to an underestimation of downside risks for airports with high concentration risk. The hypothesis that small (and large) airports may indeed recover faster from negative jumps is examined further by pooling the enplanement data by airport size.

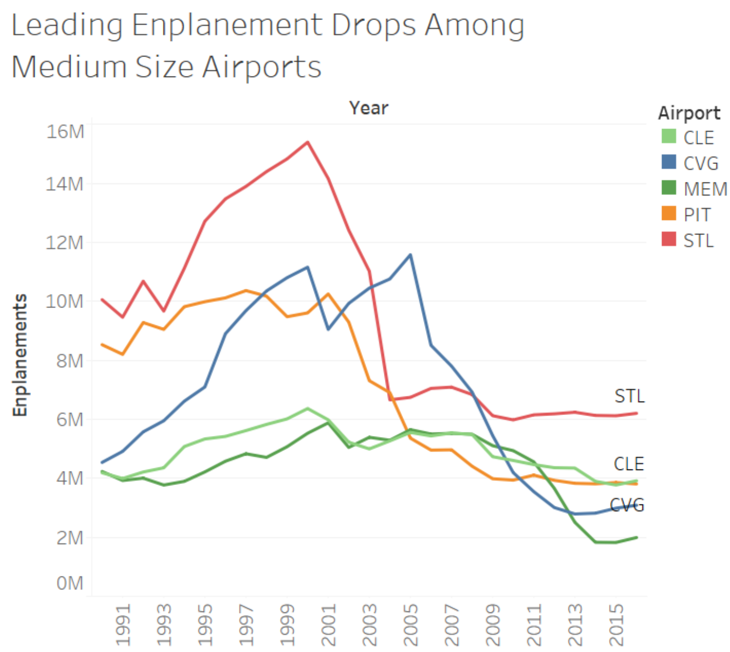

Figure 4-3 Leading enplanement drops among medium size airports

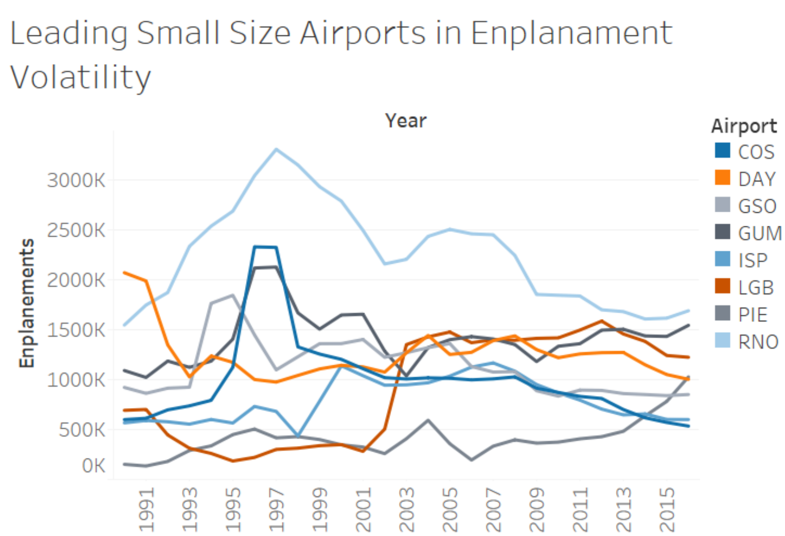

Figure 4-4 Leading enplanement drops among small size airports

An alternative representation of the relative risk medium airports may be subject to can be achieved by plotting average capacity utilization levels against the standard deviation of the same variable. Again, airport capacity utilization levels indicate considerable variation among different airport sizes, with the worst dehubbing cases for medium airports diverging from small airports (including CVG and PIT airports shown in the middle panel of Figure 4-5), despite the higher volatility of the small airports overall.

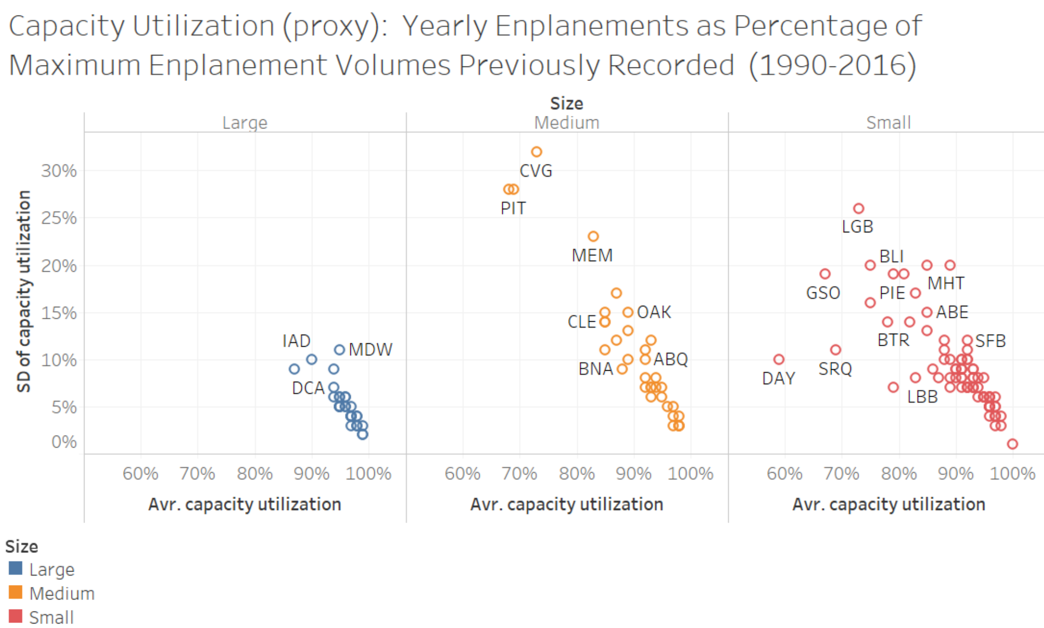

Figure 4-5 Mean and standard deviation of capacity utilization by airport size

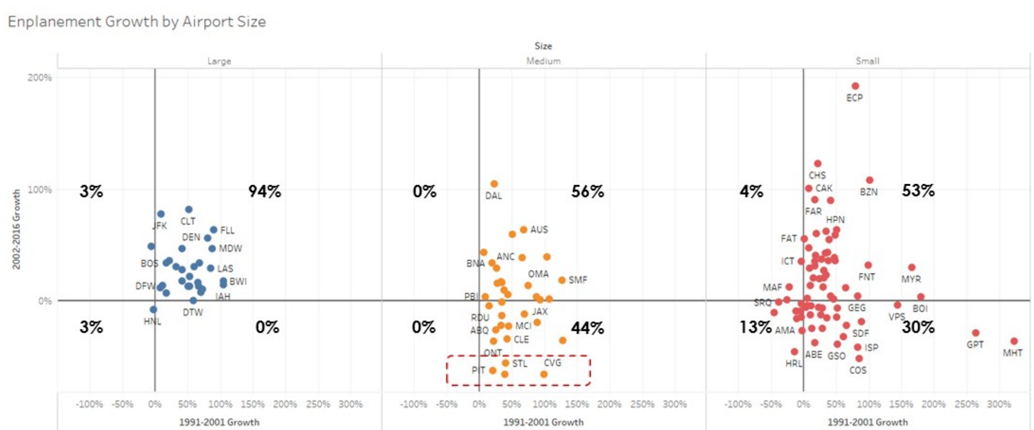

Figure 4-6 Comparison of enplanement growth before and after 2001

Another graphical representation of the relative persistence of enplanement losses for medium airports is provided in Figure 8 (aggregate enplanement growth during 1990-2001 is shown on the y-axis, whereas aggregate growth during 2002-2016 is shown on the x-axis). While large airports operated at ever increasing capacity levels over the entire sample period (almost all airports fall within the upper right quadrant in Figure 8), medium airports that experienced growth in the first half tended to undergo losses more frequently compared to smaller airports. In other words, brisk enplanement growth during the first half of the sample period was more likely to be followed by declines in the second half of the period for medium airports.

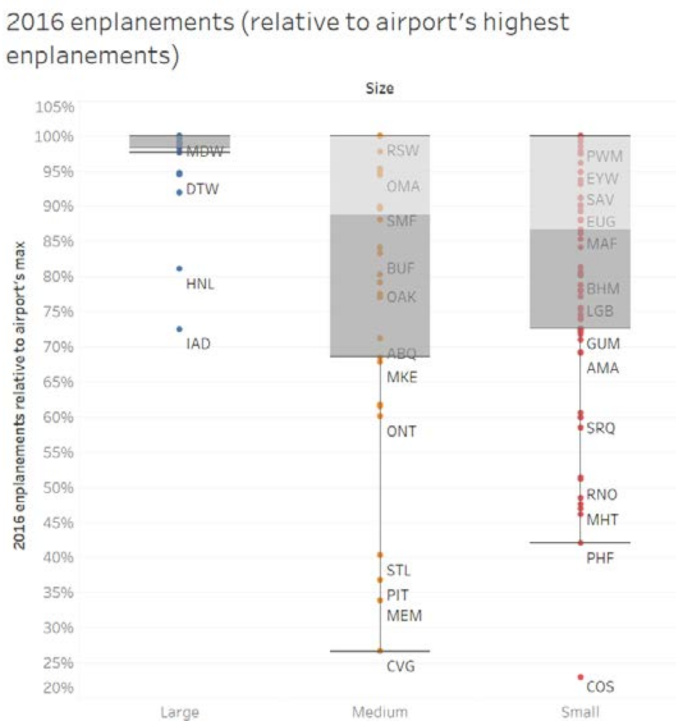

Figure 4-7 Enplanement volatility by airport size

Mean reversion

As mentioned previously, any evidence for mean reversion in capacity utilization performance has significant implications for the airports' relative ability to recover from negative jumps in demand. In the presence of a random walk process, for example, the possible range of enplanements would be expected to increase with growing variance, while stationarity in the data would suggest constant mean and variance. Consequently, quantifying Value-at-Risk levels for excess airport capacity, for example, would also depend on the stationarity of the data series. If indeed, large and small airports exhibit mean-reverting behavior, yearly growth rates can be reasonable approximations to calculate capacity at risk levels, while for medium airports, the estimates should be adjusted for lack of stationarity. In fact, the discussion provided in Part III offers one such method to calculate possible ranges for capacity use based on fitting the exponential distribution on the pooled capacity use levels.

Further, the expectation that capacity levels, in the long run, will converge toward a mean value eliminates the need for complex demand forecasting based on bottom up demand variables. Once the presence of mean reversion is established, the average capacity utilization and the anticipated time for shocks to dissipate can improve forecasts and be of considerable value for expansion projects. Note that the half-life of a process is defined as the expected duration for the process to decay to the halfway point between the post-shock and long run mean.

The autocorrelation of successive values of a time series is a strong indicator of the persistence of shocks over the long term. Time series that have a constant mean and variance over time are said to be stationary and converge to their long-term average after experiencing shocks (right panel in Figure 4-8), whereas the effect of shocks for a series following a random walk process is permanent and carried over time without decay. Any mean reversion of airport demand volumes can thus be a major factor for capital investment projects since it suggests an airport's ability to weather negative jumps in demand, such as those experienced in a dehubbing event.

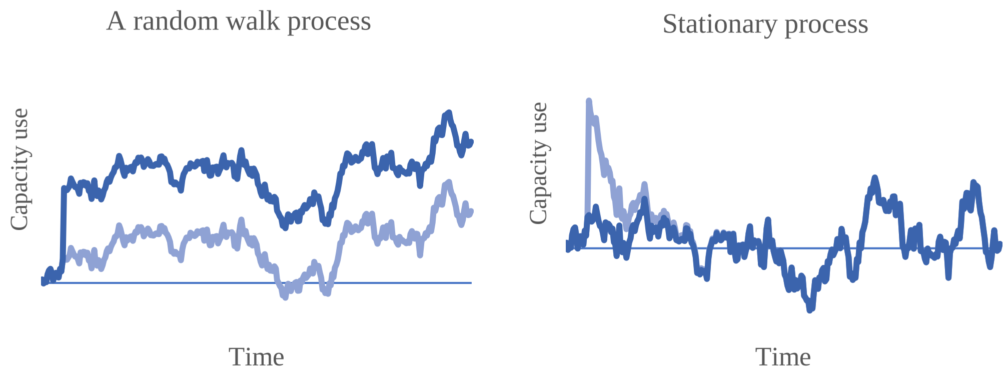

Figure 4-8 The effect of jumps under nonstationary and stationary time series

Even though the share of connecting traffic and concentration risk on hub airlines are expected to contribute to the magnitude of shocks, the long-term performance of the demand levels depends on the ability of the airport to compensate for lost demand. Thus, those airports with evidence of mean reversion in their capacity utilization levels would be expected to recover from negative shocks and attain their pre-jump levels. Mean reversion, if present, greatly facilitates the modeling of airport capacity levels because it provides a reasonable basis to expect capacity utilization levels to regress to the long term average over time. If an airport has high levels of persistence in demand level fluctuations, however, shocks are expected to have a permanent effect on excess capacity levels.

An alternative measure of an airport's ability to recover from shocks could be to verify directly if the activity levels are trend stationary. But this method would result in declaring that all enplanement volumes follow a random walk process, which would then necessitate additional measures to make the make the series stationarity before any time series analysis can be applied.

The advantages of using normalized capacity utilization levels are, therefore, twofold. Using the proxy capacity utilization measure, which is defined in the next section, not only does not require any additional steps to make the series stationary, it directly illustrates an airport's resilience to negative shocks by normalizing its operational efficiency in using its capacity over time. The normalized series can then be used to infer its future ability to employ any incremental capacity fully if additional capacity were added.

The assumption that negative shocks in the origin and destination enplanement volumes are short-lived, compared to those losses in connecting traffic, need not always apply. As noted in Chapter 3, while connecting traffic tends to be sensitive hub choices of airlines, the latter can be theorized by the trip generating capacity of the airport's catchment area. Nevertheless, when connecting traffic volumes are thought to be equally stable as the origin and destination business (as is the case for large airports) and given the industry dynamics that favor the concentration of airlines in major airports, a hub airline's departure would only have a transient effect on enplanements since the void in connecting traffic would quickly be filled by other airlines. As such, any mean reverting behavior in the capacity utilization levels are crucial to recognize because, ultimately, it is the origin and destination and connecting traffic *potential* of an airport that is expected to determine the long-term stability of an airport's capacity levels.

A proxy for airport capacity use

As mentioned in Chapter 3, an important performance measure for choosing among competing expansion strategies is expected capacity utilization, which also directly affects the operating leverage of an airport. A second type of opportunity costs—lost demand due to lack of capacity could also be considered, these are unobservable directly, and thus ignored in this analysis. The losses due to excess capacity, on the other hand, can be quite substantial. This section proposes a proxy measure for capacity utilization by normalizing each year's capacity level by the maximum service level recorded previously.

The following proxy is proposed to measure use of airport capacity use, where the *Capacity Utilization Proxy* for airport *i* in year *t* is defined by

$$\boldsymbol{Capacity\ Utilization\ Proxy}_{i,t} = \frac{enplanements_{i,t}}{\max(enplaments_{i,1990}, \ldots, enplaments_{i,t})} \qquad \textbf{Equation 4-1}$$

As Equation 4-1 indicates, while a capacity utilization of 100 percent denotes a record enplanement level in a year, lower percentages would imply the presence of excess capacity. Clearly, even though this metric will tend to underestimate the airport's true excess capacity, the resulting CUP volatility distributions offer valuable insights for the relative capacity utilization across varying hub sizes. Further, a positive bias may be still preferable because of the conservative nature of the Value-at-Risk estimates to which it leads.

Another advantage of using capacity utilization levels instead of enplanement volumes is that the latter would need first differencing to make the series stationary, as well as the estimation of an exponential time trend in the enplanements over time. Using the capacity utilization levels, however, can be directly used without any transformation to detect relative persistence in the airport enplanement data. In addition, the capacity utilization levels also do not require the inclusion of a trend component since this value is expected to be time invariant. Finally, taking the unit of analysis as the capacity utilization level also enables pooling of data to generate a distribution for capacity utilization and produce "capacity at risk" values at a given quantile. Given that most airports have undergone expansions during the sample period, the ability to test stationarity at the capacity utilization *level* has the desirable property that it can signal the continuation of the efficient use of capacity levels after adding capacity and is expected to be of immediate use for airport planners.

For each of the 140 airports in the analysis, first-order autocorrelations of the capacity proxy series are also shown in Figure 4-9 (airport-level values are listed in the appendix). To test the presence of mean reversion by airport size, yearly enplanements were normalized against the airports' running maximum historical enplanement volumes for a given year (Figure 4-10). An alternative form of visualizing this data is also provided in the appendix by using heat maps.

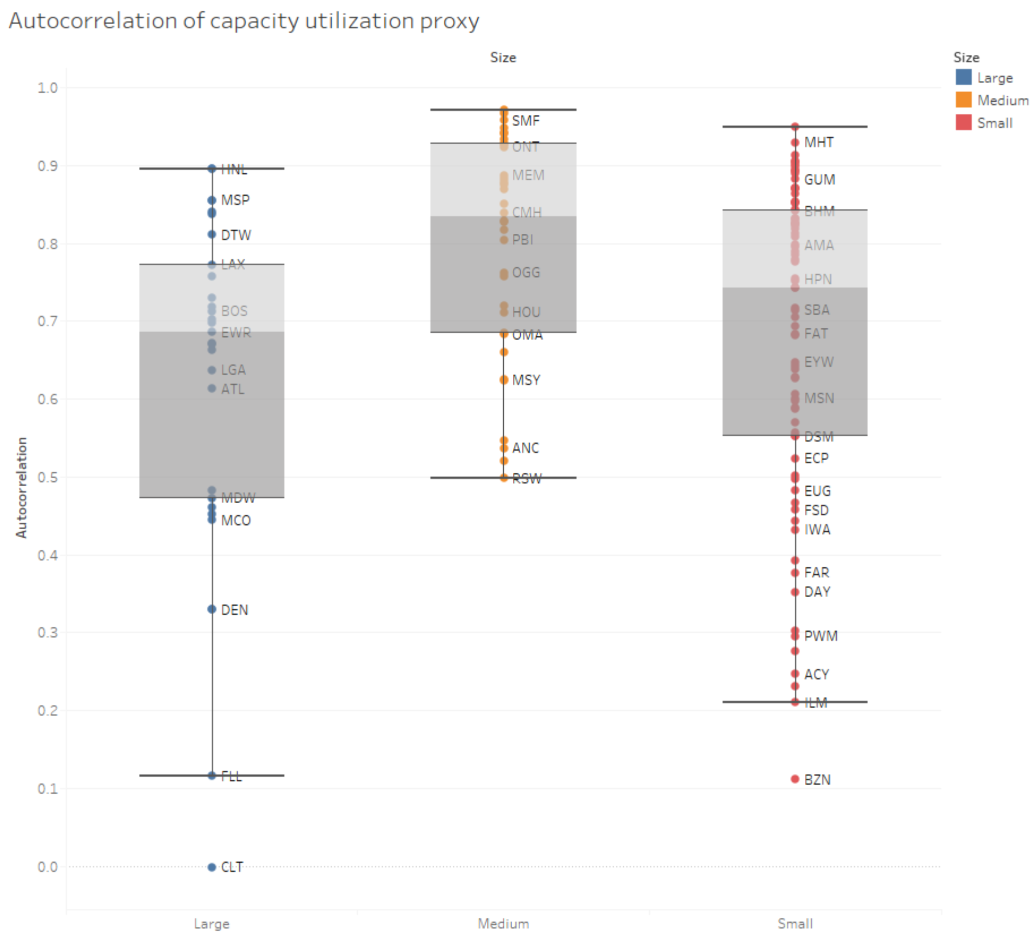

Figure 4-9 First order autocorrelations for capacity utilization by airport size

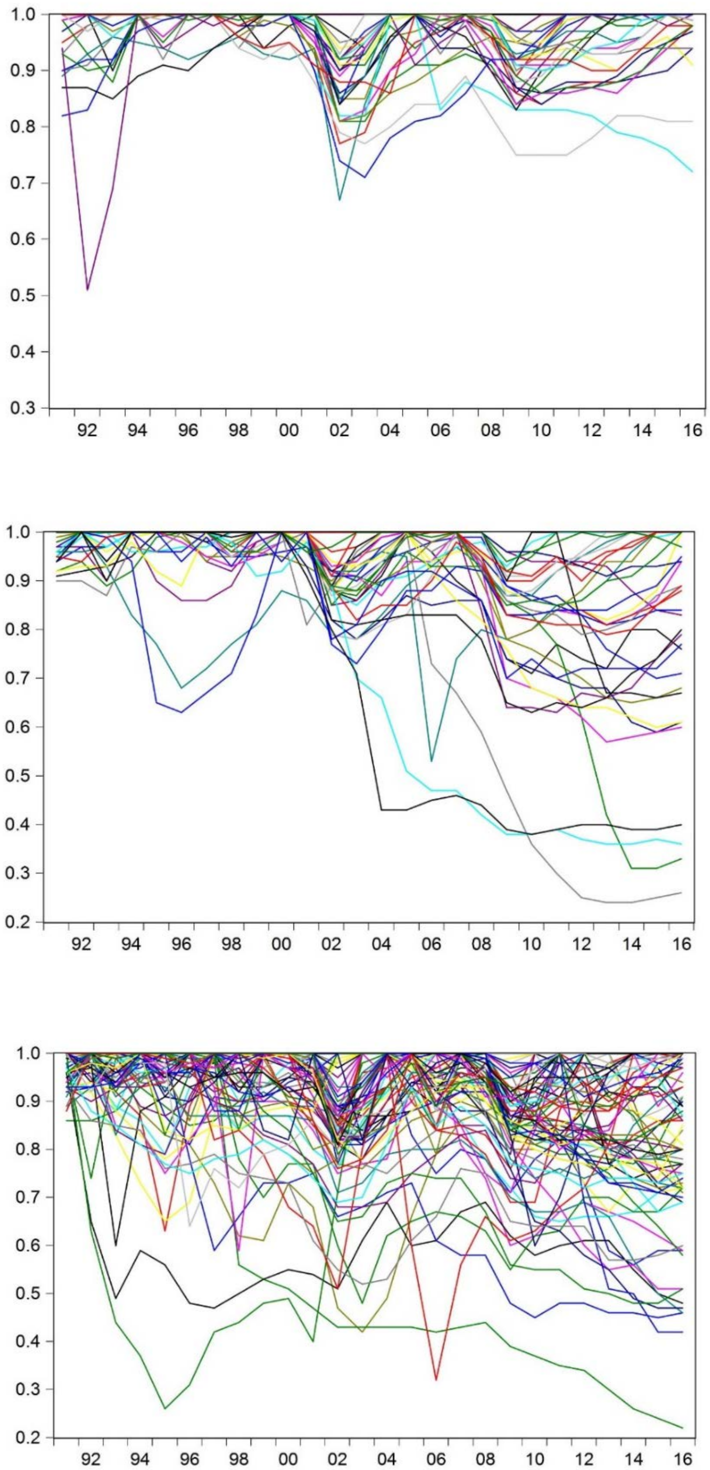

Figure 4-10 Proxy capacity utilization by airport size

(Top panel: Large airports; Mid panel: Medium airports; Bottom panel: Small airports)

Stationarity of time series

If capacity utilization levels follow a mean-reverting process and they are above the long run mean, one would expect them to go down, whereas capacity use levels below the mean would suggest future improvements in operating efficiency by converging to mean capacity utilizaiton level in the long term. The Equation 4-2 defines a simple mean reverting process.

$$\boldsymbol{C_{t+1} = C_t + a(\mu - C_t) + \varepsilon_{t+1},} \qquad \textbf{Equation 4-2}$$

where C_t is the current value of the capacity use at time t, μ is the long run average capacity utilization, a is the speed of adjustment coefficient, and ε_{t+1} is white noise. Note that $(\mu - C_t)$ represents the correction toward the long-term mean. The change in capacity use then is given by Equation 4-3.

$$\boldsymbol{\Delta C_{t+1} = a\mu - aC_t + \varepsilon_{t+1}.} \qquad \textbf{Equation 4-3}$$

If the estimated slope coefficient $-a$ above is found to be negative, then a is positive and the process is said to be mean reverting.

The above formulation is, in fact, equivalent to the first-order autoregressive process, AR(1), shown in Equations 4-4 and 4-5.

$$\boldsymbol{C_{t+1} = b_0 + \rho C_t + \varepsilon_{t+1},} \qquad \textbf{Equation 4-4}$$

which then can be modified by subtracting C_t from both sides, resulting in

$$\boldsymbol{\Delta C_{t+1} = b_0 + (\rho - 1)C_t + \varepsilon_{t+1}.} \qquad \textbf{Equation 4-5}$$

The presence of a unit root can then be tested by testing $\delta = 0$ (where $\delta = \rho - 1$). The Dickey-Fuller test tests the null hypothesis that a unit root is present ($\rho = 1$) against the alternative hypothesis that $\rho < 1$. Failure to reject the null hypothesis is equivalent to the presence of a random walk in the series, which negates the desirable properties of the ability to calculate a long run mean and chain forecasting future capacity utilization levels under a mean reverting process.

The augmented Dickey-Fuller (ADF) test further modifies the above specification by adding additional lags of higher order and adjust for autocorrelation in the series. The augmented Dickey Fuller test simply tests for the significance of the regression coefficient when the changes in series are regressed on the lagged values of itself.

The long run mean for an AR(1) process is given by Equation 4-6

$$\boldsymbol{E(C_t) = \frac{b_0}{1-\rho}.} \qquad \textbf{Equation 4-6}$$

A mean-reverting series then would tend to stay constant when $C_t = \frac{b_0}{1-\rho}$, fall when $C_t > \frac{b_0}{1-\rho}$, and rise when $C_t < \frac{b_0}{1-\rho}$.

It is clear that the average time it takes the process to revert half-way back to the long run mean depends on the speed of mean reversion, a. The higher the mean reversion speed, the shorter it takes for the capacity levels to get pulled back to the long run mean as shown in Equation 4-7.

$$\boldsymbol{h = \frac{\ln(0.5)}{\ln(|\rho|)}} \qquad \textbf{Equation 4-7}$$

Panel root tests

Panel-based unit root tests are shown to improve the limitations of unit root tests based on individual time series by providing higher power in testing for stationarity (see Greene (1993) and Baltagi (2008) for an extensive treatment of working with time series panel datasets; also, a comprehensive review of the tests employed here is presented by the EViews User's Guide, which is the statistical software package to used). The utilized capacity levels by airport size were tested for the presence of unit roots by using four alternative panel unit tests (the Levin, Lin, and Chu (LLC) test; the Im, Pesaran and Shin (IPS) test; the Fisher-PP and Fisher-ADF tests). While the Levin, Lin, and Chu (2002) test assumes a common autoregressive coefficient for the entire panel, the remaining three test allow individual coefficients in the estimated regression equations.

Consider a simple panel data specification with a first-order autoregressive component to model the airport capacity utilization levels ($c_{i,t}$) shown in Equation 4-8.

$$\boldsymbol{c_{i,t} = \delta_i + \rho_i c_{i,t-1} + \epsilon_{i,t}} \qquad \textbf{Equation 4-8}$$

where $i = 1, \dots, N$ indexes airport series, and $t = 1, \dots, T$ indexes time. The δ_i represents a constant to capture fixed effects for each airport, which effectively accounts for unobservable airport-specific capacity utilization characteristics, and $\epsilon_{i,t}$ represents independently and identically distributed noise term. If $|\rho_i| < 1$, the capacity utilization series, c_i, said to be weakly stationary, while $|\rho_i| = 1$ involves the presence unit root.

Panel-based root tests are similar to unit root tests based on individual series but produce an adjusted test statistic by essentially averaging the individual t statistics of the unit root tests for all series. Testing for unit roots is performed by either assuming a common ($\rho_i = \rho$ for all i)

or unique autoregressive behavior, which allows for ρ_i to vary across all airports. The LLC test assumes the persistence parameter to be constant for all series, while the remaining three tests (Fisher ADF and Fisher PP (Choi 2001), and Im, Pesaran and Shin (IPS) (2003)) relax this assumption by allowing for varying first order autoregressive coefficients.

All tests employ a null hypothesis of a unit root, following the standard ADF specification (Table 4-2). Although the notation for the three tests assuming individual unit root processes differ slightly, the following unit root hypothesis common to all series provide the basic ADF specification ($\alpha = \rho - 1$).

$$H_0 : \alpha = 1$$

$$H_1 : \alpha < 0$$

While under the null hypothesis, there is a unit root, under the alternative hypothesis, there is no unit root. The panel unit test results are shown in Figure 4-11.

Table 4-2 Summary of the null and alternative hypotheses under different panel unit root tests

Panel Unit Root Test	**Null (H_0)**	**Alternative (H_1)**	**Deterministic Component**
Levin, Lin and Chu (LLC)	Common unit root process	No Unit Root (UR) (all series mean reverting)	Individual intercept (Fixed effects)
Im, Pesaran and Shin (IPS)	Individual unit root process	Some cross-sections without UR (some series mean reverting)	Individual intercept (Fixed effects)
Fisher-PP	Individual unit root process	Some cross-sections without UR (some series mean reverting)	Individual intercept (Fixed effects)
Fisher-ADF	Individual unit root process	Some cross-sections without UR (some series mean reverting)	Individual intercept (Fixed effects)

Panel Unit Tests for Large Airports

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t	-6.47	**0.0000**	29	708
Null: Unit root (assumes individual unit root process)				
IPS W-stat	-7.36	**0.0000**	29	708
ADF - Fisher Chi-square	166.09	**0.0000**	29	708
PP - Fisher Chi-square	147.40	**0.0000**	29	725

Panel Unit Root Tests for Medium Airports

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.03	0.84	34	831
Null: Unit root (assumes individual unit root process)				
IPS W-stat	-0.19	0.42	34	831
ADF - Fisher Chi-square	9.31	**0.04**	34	831
PP - Fisher Chi-square	60.13	0.74	34	850

Panel Unit Root Tests for Small Airports

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.69	0.24	76	1848
Null: Unit root (assumes individual unit root process)				
IPS W-stat	-2.91	**0.0018**	76	1848
ADF - Fisher Chi-square	231.24	**0.0000**	76	1848
PP - Fisher Chi-square	237.89	**0.0000**	76	1880

Figure 4-11 Panel unit root tests by airport size

Based on the results documented in Figure 4-11, the presence of mean reversion is strongest for large airports since the null hypothesis that the panel has unit roots is soundly rejected under both of the assumptions (that the panel has a common or individual unit processes). Next, small airports are also shown to have stationary capacity utilization levels under the assumption of an existence of individual unit root processes. Two of the three tests that assume individual root processes for medium airports, in contrast, suggest that the presence of unit roots even when allowing for individual coefficients cannot be rejected. Combined with the failure to reject the null hypothesis for the entire panel, the medium airports thus provide the clearest evidence for the random walk nature of their capacity utilization levels.

The implication of these findings is that large and small airports seem to be better equipped to weather jumps in airport activity volumes. The results provide significant evidence that the need for flexible designs for medium airports is even more crucial to offset any potential losses they may incur in their activity levels.

Capacity at risk

Drawing a parallel between a widely accepted risk measure (see Chambers (2007) for an example of how airport planning can apply the Value-at-Risk concept in practice), that is used to communicate a portfolio's exposure to potential losses for a given level of confidence, this section offers a similar risk measure to quantify an airport's exposure to underutilized capacity. Given the considerable downside risks observed both in the distribution of yearly changes in enplanements and capacity utilization, standard measures of Value-at-Risk may be inadequate in quantifying potential losses for airport operators. Thus, this section considers the magnitude of losses given a certain level of excess capacity.

Capacity at risk in a single year

Even though the best fit distribution for the volatility of annual enplanement growth rates (Figure 4-12) is the Student's t distribution, with low values of ν, suggesting fatter tails than the normal distribution, the following equation (which is based on the assumption that rates are normally distributed) can be used to approximate capacity at risk at α percent level of confidence in a single year.

$$\boldsymbol{VaR = W(\sigma - \mu)z} \qquad \textbf{Equation 4-9}$$

where W indicates mean passenger enplanements, μ is the mean growth rate, z is the z-value corresponding to the α percent confidence level for a standard normal distribution, and σ is the standard deviation of enplanement growth. For airports that are believed to follow a random walk process, capacity at risk values for short periods covering multiple years can also be approximated by multiplying the value obtained for a single year by the square root of the desired number of years.

Capacity at risk over the life of a project

If the 26-year period considered here is accepted as the period over which airport capacity levels would reasonably fluctuate, capacity at risk levels can be approximated by the resulting probability distribution of pooled growth rates for each airport category. As suggested by the histograms of capacity utilization levels both at the individual (available in the appendix) and aggregate (Figures 4-12 and 4-13) level, the exponential distribution seems to provide a reasonable approximation process to characterize the distribution of airport excess capacity. In fact, a visual check of the exponential distributions fit for several airports suggests that ($\beta = 1/\lambda$) average excess capacity level for a given airport, $\beta = Exp(1 - C_{it})$, indeed produces the expected density distributions with zero percent excess capacity levels matching the theoretical rate parameter of $\lambda = 1/\beta$.

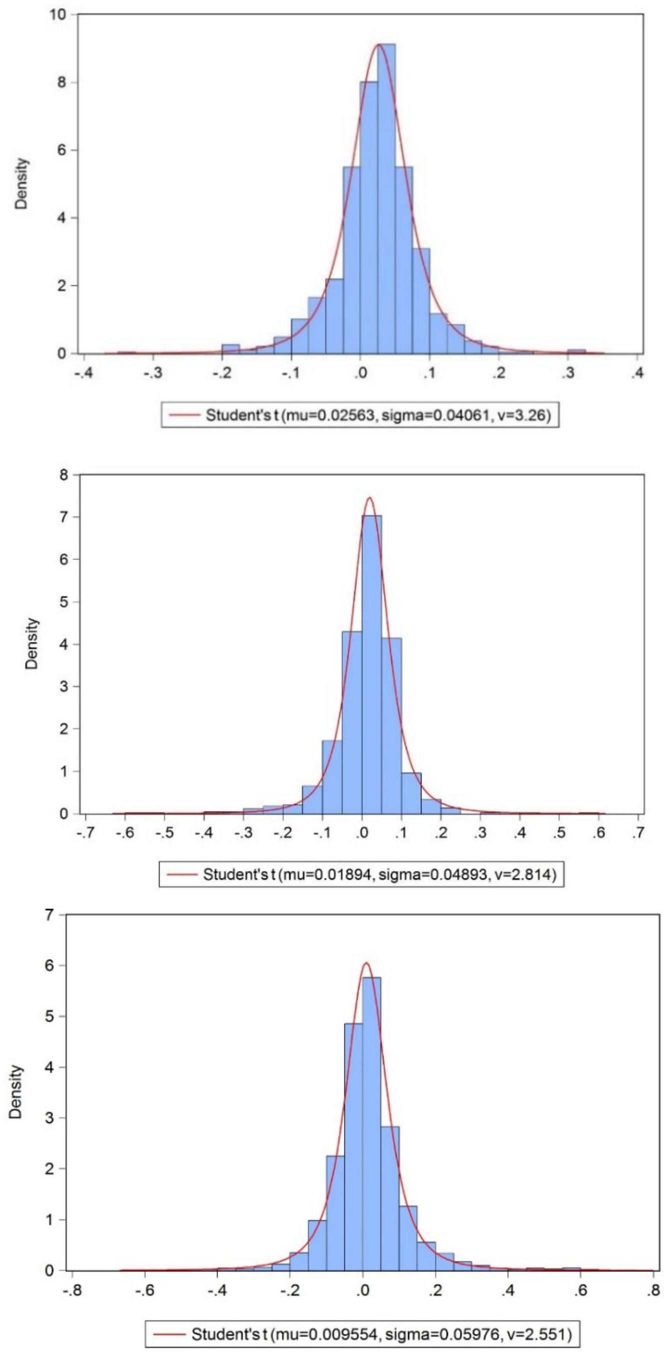

Figure 4-12 Enplanement growth volatility by airport size

(Top panel: Large airports; Mid panel: Medium airports; Bottom panel: Small airports)

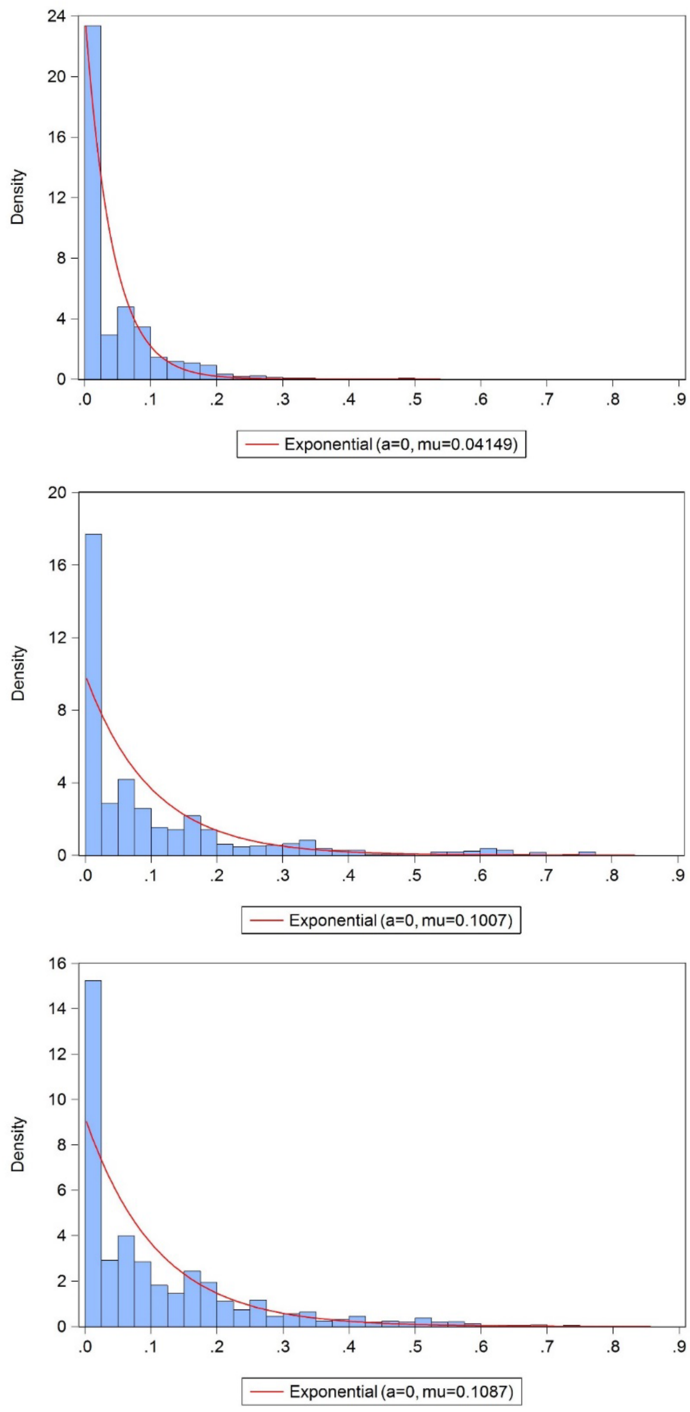

Figure 4-13 Pooled excess capacity levels by airport size (Top panel: Large airports; Mid panel: Medium airports; Bottom panel: Small airports)

A potential explanation for this result is that since the exponential distribution describes the time between events in a Poisson process, the excess capacity histograms represent the survival duration of the no-excess-capacity events, i.e., the waiting time between years of no excess airport capacity. It should be noted that the exponential distribution is defined by a single variable—rate parameter (λ), which is equivalent to the average of negative events that lead to excess capacity. If the average event causes a β percent excess capacity, then λ, the rate parameter, is equivalent to the density of no-excess-capacity events (i.e., years where the observed enplanement levels exceed the previously recorded maximum activity levels).

This observation greatly facilitates the formulation of a hypothetical, yet reasonable, capacity use levels for airports. This distribution can then be used to generate potential "capacity at risk" values to inform decisions in expansion investments.

The probability density function for the exponential distribution is given by Equation 4-10:

$$\boldsymbol{f(x;\lambda) = \lambda e^{-\lambda x}, \quad x \geq 0} \qquad \textbf{Equation 4-10}$$

The cumulative distribution function is given by Equation 4-11:

$$\boldsymbol{F(x;\lambda) = 1 - e^{-\lambda x}, \quad x \geq 0} \qquad \textbf{Equation 4-11}$$

Finally, once a desired level of confidence (p) and λ are given, $F^{-1}(p;\lambda)$ can be calculated by Equation 4-12, which then leads to an expected capacity at risk value over the life of the project shown in Equation 4-13.

$$\boldsymbol{F^{-1}(p;\lambda) = \frac{-ln(1-p)}{\lambda}, \quad 0 \leq x < 1} \qquad \textbf{Equation 4-12}$$

$$\boldsymbol{VaR = WF^{-1}(p;\lambda)} \qquad \textbf{Equation 4-13}$$

where W is the mean passenger enplanements for the airport of interest. It should be noted that the formula provided here can only serve as a rough benchmark in quantifying the downside exposure for airports, and is most applicable for a hypothetical airport that represents the average excess capacity in its size category. That is, as it should be clear from the excess capacity graphs provided for individual airports in the appendix, the capacity at risk formula would still fall short of providing the type of losses experienced by those airports with significant dehubbing activity. Equation 4-13 also puts potential losses in perspective by multiplying airport activity volumes with a quantile function. As a result, potential downside exposures that drive the value of flexibility options can vary among airports of different sizes. Flexibility options for a large airport, for instance, can be valued to be higher than they would be for an airport with much higher levels of volatility due to the former's exceedingly large enplanement volumes (W).

Conclusions

The paper's analysis, supported by the use of panel root tests, suggests that capacity use performance for medium airports may be uniquely different from their peers in small and large size categories. While excess capacity levels, normalized against an airport's previously recorded maximum enplanement volumes, show strong evidence for stationarity for large and small airports, for medium airports, capacity utilization time series follow a random walk process. Even the worst cases of enplanement losses for small airports have been relatively milder and shorter in duration compared to their peers in the medium category, even though the former has higher levels of enplanement growth volatility. Small airports, as a result, are expected to be relatively immune from the dramatic losses experienced by the medium airports, due to their limited connecting traffic volumes.

Again, despite showing relatively stable enplanement levels compared to small airports, therefore, medium airports seem to be exposed to considerably higher downside risks as they accumulate the effects of negative shocks to their activity levels. Higher conditional at risk values are in agreement with a random walk process for medium airports. Consequently, for medium airports, when negative shocks do occur, they are expected to last longer than those experienced by larger and smaller airports. As expected, large airports exhibit the most stable enplanement patterns out of the three sizes examined here.

This finding, combined with the relative ease for medium airports to acquire flexibility options in their expansion plans vis-à-vis smaller airports, positions them favorably in employing flexible timing and design approaches in their planning efforts for airport capital improvements. Simply stated, while large airports are expected to have access to the broadest array of flexible expansion options, their mean reverting capacity performance and low levels of growth volatility may diminish the urgency of using such options. In contrast, the persistence of losses and the ability to offset them by employing flexible design options make the use of an option-based planning approach essential for medium airports. These nonlinear results with respect to airport size can arguably provide valuable insights for airport planners in their forecasting of airport capacity use following expansion projects.

A potential explanation for the lack of mean reverting behavior for medium airports could be the relatively transient nature of their connecting traffic. For instance, it may be argued that the reason for mean reversion for large and small is that while the former has substantial connecting traffic volumes, such business is stable given their hub status, whereas the medium airports cannot compensate for their losses post dehubbing. Small airports may also show mean reversion because they lack the requisite connecting traffic in the first place. Therefore, further exploration of connecting traffic volumes, concentration risk, and capacity utilization levels are identified as promising topics for future research.

CHAPTER 5. CONCLUSIONS, CONTRIBUTIONS, AND RECOMMENDATIONS

Introduction

The perpetual options framework, despite its shortcomings due to a strong set of assumptions that reflects the behavior of financial assets, provides a succinct model that highlights the anticipated effects of a number of important project variables. Such factors include the volatility of project valuations, initial investment costs, discount rates, and project cash payouts that are essential to any investment analysis.

As it has been emphasized throughout, this research underlines the volatility in engineering decision variables as a source of value for managers. Clearly, tapping into the option value of uncertainty in engineering investments should start with a sound understanding of volatility in valuation parameters and the driving mechanisms behind such uncertainty. Unlike the relatively static perspectives adopted in standard management practices for engineering assets, an options-based framework stretches the valuation boundaries to capture option values due to the presence of uncertainties present in the projects' life cycles. It can be argued that managers not only need tools to recognize these types of uncertainties, as this study attempts to do, but they need the ability to embed such options early in planning phases before they can be exercised at a future date. The following list offers the main findings of the three papers that make up this dissertation.

Conclusions

Chapter 2

When alternative design methods are chosen on the basis of an expected price differential between them, the threshold to trigger investment decisions should be an increasing function of the volatility of cost differences between the competing alternatives. In other words, as the uncertainty over which alternative provides the best cost savings mounts, the threshold levels to make outright design decisions should also increase.

Chapter 3

Flexibility in investment timing may provide option values that may otherwise not be captured in traditional NPV analyses. Given the substantial volatility observed in US passenger enplanements both over time and between the three (large, medium, and small) airport categories, airport expansion options would benefit from a valuation approach that makes volatility dynamics a focal point. In particular, two types of flexibilities in expansion options—flexibility in investment timing, and flexibility in engineering design—can offer substantial benefits for airport operators both to position their expansion plans for potential growth and to their downside exposures.

Chapter 4

By performing a number panel root tests, the paper provides statistically significant evidence for the presence of mean reverting behavior for large and small airports. To obtain this result, growth rates for each of the 140 airports were normalized against an airport's running maximum enplanement levels. While large hubs tended to operate at "capacity" over the 26-year sample period, at least four medium hubs witnessed significant dehubbing events, from which they have recovered only slightly. Small hubs, in contrast, witnessed relatively milder and shorter episodes of jumps in demand.

Stationary behavior in capacity utilization levels is important for two reasons. First, excess capacity signals the inefficient use of airports' capital resources *ex-post*. Second, the presence of a stationary time series may greatly simplify future capacity forecasts for large and small airports if they are indeed relatively resilient to sizeable shocks to their activity levels, such as the departures of a major airline client. Although modeling jumps in airport activity remains a significant challenge, the paper's finding on the nonlinear nature of the relationship between airport size and mean reversion highlights the need for future research to explore the contributing role of connecting traffic levels to this outcome. In light of the medium airports' heightened exposures to downside risks, they may reap significant benefits from flexible planning approaches, especially if they can adapt their facilities to new functional requirements. Finally, based on the reasonableness of fitting the exponential distributions on pooled airport growth data for the 26-year study period, the paper suggests that the exponential distribution may be used as a rough approximation for, what the paper calls, the "capacity at risk" values for a given level of confidence.

Contributions

The major contribution of the study is the explicit formulation of an equation for airport activity levels, which relates jumps in passenger enplanements to the valuation of airport expansions. It is shown that airport expansion projects, when conceptualized as a series of investments that permits modularity in design, such as those adding gateways to a terminal building, would benefit from dynamic investment decision rules that monitor and act upon sustained trends in demands, which are similar in function to the optimal investment thresholds in perpetual options. Jumps in enplanement demand, in particular, are linked to the "concentration risk" of an airport in losing a particular airlines' business. Further, by breaking enplanement demand into two separate components—origin and destination, and connecting traffic—the proposed enplanement demand model is capable of accommodating the time-varying exposure by adjusting the magnitude of jumps in demand.

In line with the irreversibility assumption common in the real options literature (McDonald 2006, Pindyck 1986), excess capacity levels are determined as a major type of opportunity costs that should be considered in the valuation of expansion projects. Since expansion projects are expected to burden airports both with servicing the debt for initial capital expenditures, and ongoing operation and maintenance expenses for extended time periods, the benefits of acquiring flexibility options to manage downside risks to excess capacity becomes self-evident.

Thus, rather than a narrow focus on calculating expected NPV values alone, this study seeks to examine whether capacity utilization levels over time contain any information that may contribute to the planning and forecasting needs of airport operators. If there is evidence for mean-reverting behavior for some airport groups, as this study argues, then future capacity levels cannot only be forecastable, but the speed to which capacity levels would be expected to converge to the long run mean could also be estimated. Knowing that some airports may not recover from unexpected setbacks to their activity levels suggests that planning for expansion projects should use extra caution in considering acquiring flexibility options for their capital investment plans.

The study also identifies an excess capacity proxy measure as an important type of efficiency metric, since low capacity utilization following expansion projects is considered to be a key opportunity cost with important valuation implications.

When there is considerable complexity, as there is in the case of airports (Horonjeff et al. 2010; de Neufville et al. 2013; Reynolds et al. 2013; Spitz and Golaszewski 2007; Trani 2002), time series analysis may provide valuable insights for both forecasting future capacity use following airport expansion projects, simplifying the calculation of a relatively stable mean and variance over the long run. To this end, any evidence for the stationarity of capacity use levels across different airport categories is examined through the application of panel root tests. By employing a panel time series dataset of considerable size, which covers the enplanement data for the largest 140 US airports over the period from 1990 to 2016 (FAA Terminal Area Forecast 2016), the study provides a unique perspective on the relative enplanement growth rates among three airport categories of size defined by the Federal Aviation Administration (FAA).

The results suggest the presence of a statistically significant nonlinear relationship between airport size and stationarity of airport capacity use. It is argued that the existence or lack of persistence in excess capacity levels lead to distinct valuation dynamics for airports of different sizes. Despite medium size airports' relatively low volatility of growth rates, relative to small airports, the evidence for the persistence of negative jumps in demand (due to major dehubbing events, for instance) underscores the importance of flexibility options to convert excess capacity into new functional requirements in adapting to a shifting business environment. These airports may not only have the land the large airports may lack, but they have the ability to attract sustained demand to their facilities by competing for emerging functional needs in the industry, which are arguably lacked by small airports.

Finally, the enplanement growth rates are pooled to generate "capacity at risk" volumes at a given level of confidence. It is argued that the exponential function should provide a reasonable approximating of the excess capacity exposure of an expansion project if there is evidence that the historical capacity utilization levels have been stationary. Capacity at risk can provide valuable insights into both the aggregate risks airport managers are believed to be carrying, and into any incremental exposures that would be introduced with expanding existing airport capacity. This way, a normalized risk measure can facilitate comparisons between airports with highly different enplanement and volatility levels (Granger and Henrion 1990).

It should be noted that there has been no attempt made to break the 26-year sample period into segments to investigate whether there have been structural shifts in the data. It may be argued, for instance, that the 9/11 terror attacks in 2001 and the financial crisis of 2008 have influenced the aviation business in ways that triggered bankruptcies and rapid mergers and consolidation activity. However, given both the sustained growth trends in air traffic and airport activity levels (FAA 2004), any structural shifts airlines may have experience at the industry level are not expected to be equally disruptive for airport operators when the largest 140 airports are studied in aggregate.

Recommendations for future research

The results indicate the need for further research in studying the causes of the nonlinear relationship between size and capacity utilization. A potential explanatory mechanism could relate to the airports' ability to attract and retain connecting passenger traffic. Large airports may be relatively immune from losing large shares of their connecting traffic through the departure of a hub airline because the resulting enplanement losses would be compensated swiftly by other airlines. Therefore, an immediate extension of this research could be analyzing the airport operators' concentration risk and share of connecting traffic at the airport level.

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APPENDIX TABLES AND FIGURES

Table A1. List of airports (large)

Airport ID	Airport Name	City
ATL	HARTSFIELD - JACKSON ATLANTA INTL	ATLANTA, GA
BOS	GENERAL EDWARD LAWRENCE LOGAN INTL	BOSTON, MA
BWI	BALTIMORE/WASHINGTON INTL	BALTIMORE, MD
CLT	CHARLOTTE/DOUGLAS INTL	CHARLOTTE, NC
DCA	RONALD REAGAN WASHINGTON NATIONAL	WASHINGTON, DC
DEN	DENVER INTL	DENVER, CO
DFW	DALLAS/FORT WORTH INTL	DALLAS-FORT WORTH, TX
DTW	DETROIT METROPOLITAN WAYNE COUNTY	DETROIT, MI
EWR	NEWARK LIBERTY INTL	NEWARK, NJ
FLL	FORT LAUDERDALE/HOLLYWOOD INTL	FORT LAUDERDALE, FL
HNL	HONOLULU INTL	HONOLULU, HI
IAD	WASHINGTON DULLES INTL	WASHINGTON, DC
IAH	GEORGE BUSH INTERCONTINENTAL/HOUSTON	HOUSTON, TX
JFK	JOHN F KENNEDY INTL	NEW YORK, NY
LAS	MC CARRAN INTL	LAS VEGAS, NV
LAX	LOS ANGELES INTL	LOS ANGELES, CA
LGA	LAGUARDIA	NEW YORK, NY
MCO	ORLANDO INTL	ORLANDO, FL
MDW	CHICAGO MIDWAY INTL	CHICAGO, IL
MIA	MIAMI INTL	MIAMI, FL
MSP	MINNEAPOLIS-ST PAUL INTL	MINNEAPOLIS, MN
ORD	CHICAGO O'HARE INTL	CHICAGO, IL
PHL	PHILADELPHIA INTL	PHILADELPHIA, PA
PHX	PHOENIX SKY HARBOR INTL	PHOENIX, AZ
SAN	SAN DIEGO INTL	SAN DIEGO, CA
SEA	SEATTLE-TACOMA INTL	SEATTLE, WA
SFO	SAN FRANCISCO INTL	SAN FRANCISCO, CA
SLC	SALT LAKE CITY INTL	SALT LAKE CITY, UT
TPA	TAMPA INTL	TAMPA, FL

Table A2. List of airports (medium)

Airport ID	Airport Name	City
ABQ	ALBUQUERQUE INTL SUNPORT	ALBUQUERQUE, NM
ANC	TED STEVENS ANCHORAGE INTL	ANCHORAGE, AK
AUS	AUSTIN-BERGSTROM INTL	AUSTIN, TX
BDL	BRADLEY INTL	WINDSOR LOCKS, CT
BNA	NASHVILLE INTL	NASHVILLE, TN
BUF	BUFFALO NIAGARA INTL	BUFFALO, NY
BUR	BOB HOPE	BURBANK, CA
CLE	CLEVELAND-HOPKINS INTL	CLEVELAND, OH
CMH	PORT COLUMBUS INTL	COLUMBUS, OH
CVG	CINCINNATI/NORTHERN KENTUCKY INTL	COVINGTON , KY
DAL	DALLAS LOVE FIELD	DALLAS, TX
HOU	WILLIAM P HOBBY	HOUSTON, TX
IND	INDIANAPOLIS INTL	INDIANAPOLIS, IN
JAX	JACKSONVILLE INTL	JACKSONVILLE, FL
MCI	KANSAS CITY INTL	KANSAS CITY, MO
MKE	GENERAL MITCHELL INTL	MILWAUKEE, WI
MSY	LOUIS ARMSTRONG NEW ORLEANS INTL	NEW ORLEANS, LA
OAK	METROPOLITAN OAKLAND INTL	OAKLAND, CA
OGG	KAHULUI	KAHULUI, HI
OMA	EPPLEY AIRFIELD	OMAHA, NE
ONT	ONTARIO INTL	ONTARIO, CA
PDX	PORTLAND INTL	PORTLAND, OR
PBI	PALM BEACH INTL	WEST PALM BEACH, FL
PIT	PITTSBURGH INTL	PITTSBURGH, PA
RDU	RALEIGH-DURHAM INTL	RALEIGH/DURHAM, NC
RSW	SOUTHWEST FLORIDA INTL	FORT MYERS, FL
SAT	SAN ANTONIO INTL	SAN ANTONIO, TX
SJC	NORMAN Y MINETA SAN JOSE INTL	SAN JOSE, CA
SJU	LUIS MUNOZ MARIN INTL	SAN JUAN, PR
SMF	SACRAMENTO INTL	SACRAMENTO, CA
SNA	JOHN WAYNE AIRPORT-ORANGE COUNTY	SANTA ANA, CA
STL	LAMBERT-ST LOUIS INTL	ST LOUIS, MO

Table A3. List of airports (small)

Airport ID	Airport Name	City
ACY	ATLANTIC CITY INTL	ATLANTIC CITY, NJ
ALB	ALBANY INTL	ALBANY, NY
AVL	ASHEVILLE RGNL	ASHEVILLE, NC
BHM	BIRMINGHAM-SHUTTLESWORTH INTL	BIRMINGHAM, AL
BIL	BILLINGS LOGAN INTL	BILLINGS, MT
BLI	BELLINGHAM INTL	BELLINGHAM, WA
BOI	BOISE AIR TERMINAL/GOWEN FLD	BOISE, ID
BTV	BURLINGTON INTL	BURLINGTON, VT
BZN	BOZEMAN YELLOWSTONE INTL	BOZEMAN, MT
CAE	COLUMBIA METROPOLITAN	COLUMBIA, SC
CAK	AKRON-CANTON RGNL	AKRON, OH
CHA	LOVELL FIELD	CHATTANOOGA, TN
CHS	CHARLESTON AFB/INTL	CHARLESTON, SC
CID	THE EASTERN IOWA	CEDAR RAPIDS, IA
COS	CITY OF COLORADO SPRINGS MUNI	COLORADO SPRINGS, CO
DAY	JAMES M COX DAYTON INTL	DAYTON, OH
DSM	DES MOINES INTL	DES MOINES, IA
ECP	NORTHWEST FLORIDA BEACHES INTL	PANAMA CITY, FL
ELP	EL PASO INTL	EL PASO, TX
EUG	MAHLON SWEET FIELD	EUGENE, OR
FAI	FAIRBANKS INTL	FAIRBANKS, AK
FAR	HECTOR INTL	FARGO, ND
FAT	FRESNO YOSEMITE INTL	FRESNO, CA
FNT	BISHOP INTL	FLINT, MI
FSD	JOE FOSS FIELD	SIOUX FALLS, SD
GEG	SPOKANE INTL	SPOKANE, WA
GRR	GERALD R FORD INTL	GRAND RAPIDS, MI
GSN	FRANCISCO C ADA/SAIPAN INTL	SAIPAN ISLAND, MP
GSO	PIEDMONT TRIAD INTL	GREENSBORO, NC
GSP	GREENVILLE SPARTANBURG INTL	GREER, SC
GUM	GUAM INTL	GUAM, GU
HPN	WESTCHESTER COUNTY	WHITE PLAINS, NY
HSV	HUNTSVILLE INTL-CARL T JONES FIELD	HUNTSVILLE, AL
ICT	WICHITA DWIGHT D EISENHOWER NATIONAL	WICHITA, KS
ISP	LONG ISLAND MAC ARTHUR	NEW YORK, NY
ITO	HILO INTL	HILO, HI
IWA	PHOENIX-MESA GATEWAY	PHOENIX, AZ
JAN	JACKSON-MEDGAR WILEY EVERS INTL	JACKSON, MS
KOA	KONA INTL AT KEAHOLE	KAILUA/KONA, HI
LBB	LUBBOCK PRESTON SMITH INTL	LUBBOCK, TX
LEX	BLUE GRASS	LEXINGTON, KY

Airport ID	Airport Name	City
LGB	LONG BEACH /DAUGHERTY FIELD/	LONG BEACH, CA
LIH	LIHUE	LIHUE, HI
LIT	CLINTON NATIONAL/ADAMS FIELD	LITTLE ROCK, AR
MAF	MIDLAND INTL	MIDLAND, TX
MDT	HARRISBURG INTL	HARRISBURG, PA
MEM	MEMPHIS INTL	MEMPHIS, TN
MFE	MC ALLEN MILLER INTL	MC ALLEN, TX
MHT	MANCHESTER	MANCHESTER, NH
MSN	DANE COUNTY RGNL-TRUAX FIELD	MADISON, WI
MYR	MYRTLE BEACH INTL	MYRTLE BEACH, SC
OKC	WILL ROGERS WORLD	OKLAHOMA CITY, OK
ORF	NORFOLK INTL	NORFOLK, VA
PGD	PUNTA GORDA	PUNTA GORDA, FL
PIE	ST PETE-CLEARWATER INTL	ST PETERSBURG, FL
PNS	PENSACOLA INTL	PENSACOLA, FL
PSP	PALM SPRINGS INTL	PALM SPRINGS, CA
PVD	THEODORE FRANCIS GREEN STATE	PROVIDENCE, RI
PWM	PORTLAND INTL JETPORT	PORTLAND, ME
RIC	RICHMOND INTL	RICHMOND, VA
RNO	RENO/TAHOE INTL	RENO, NV
ROC	GREATER ROCHESTER INTL	ROCHESTER, NY
SAV	SAVANNAH/HILTON HEAD INTL	SAVANNAH, GA
SDF	LOUISVILLE INTL-STANDIFORD FIELD	LOUISVILLE, KY
SFB	ORLANDO SANFORD INTL	ORLANDO, FL
SGF	SPRINGFIELD-BRANSON NATIONAL	SPRINGFIELD, MO
SRQ	SARASOTA/BRADENTON INTL	SARASOTA/BRADENTON , FL
STT	CYRIL E KING	CHARLOTTE AMALIE, VI
SYR	SYRACUSE HANCOCK INTL	SYRACUSE, NY
TTN	TRENTON MERCER	TRENTON, NJ
TUL	TULSA INTL	TULSA, OK
TUS	TUCSON INTL	TUCSON, AZ
TYS	MC GHEE TYSON	KNOXVILLE, TN
XNA	NORTHWEST ARKANSAS RGNL	FAYETTEVILLE, AR

Airport	Code	2005 Total Enplaned Passengers	2015 Total Enplaned Passengers	Percent change 2005-2015
Cleveland, OH (Cleveland-Hopkins International)	CLE	5,592,663	3,955,494	-29.3
Pittsburgh, PA (Pittsburgh International)	PIT	5,279,410	3,950,675	-25.2
Oakland, CA (Metropolitan Oakland International)	OAK	7,352,229	5,689,426	-22.6
San Juan, PR (Luis Munoz Marin International)	SJU	5,389,775	4,271,558	-20.7
Washington, DC (Washington Dulles International)	IAD	13,154,681	10,440,911	-20.6
St. Louis, MO (Lambert-St. Louis International)	STL	7,232,239	6,486,985	-10.3
San Jose, CA (Norman Y. Mineta San Jose International)	SJC	5,444,412	4,903,715	-9.9
Milwaukee, WI (General Mitchell International)	MKE	3,665,420	3,318,610	-9.5
Indianapolis, IN (Indianapolis International)	IND	4,309,634	3,960,509	-8.1
Detroit, MI (Detroit Metro Wayne County)	DTW	17,775,420	16,338,390	-8.1
Sacramento, CA (Sacramento International)	SMF	5,218,724	4,810,107	-7.8
Honolulu, HI (Honolulu International)	HNL	10,213,207	9,579,087	-6.2
Kansas City, MO (Kansas City International)	MCI	5,509,973	5,293,009	-3.9
Philadelphia, PA (Philadelphia International)	PHL	15,724,402	15,210,085	-3.3
Minneapolis, MN (Minneapolis-St Paul International)	MSP	18,155,103	17,753,814	-2.2
Chicago, IL (Chicago O'Hare International)	ORD	37,097,875	36,490,096	-1.6
Tampa, FL (Tampa International)	TPA	9,462,465	9,310,599	-1.6
Salt Lake City, UT (Salt Lake City International)	SLC	10,851,666	10,697,496	-1.4
Columbus, OH (Port Columbus International)	CMH	3,327,647	3,360,186	1.0
Las Vegas, NV (McCarran International)	LAS	21,860,911	22,097,505	1.1
Phoenix, AZ (Phoenix Sky Harbor International)	PHX	21,247,905	21,935,329	3.2
Santa Ana, CA (John Wayne Airport-Orange County)	SNA	4,824,502	4,999,142	3.6
Raleigh/Durham, NC (Raleigh-Durham International)	RDU	4,762,982	5,002,315	5.0
Houston, TX (George Bush Intercontinental/Houston)	IAH	19,148,363	20,771,968	8.5
New York, NY (LaGuardia)	LGA	13,025,007	14,333,938	10.0
Fort Myers, FL (Southwest Florida International)	RSW	3,764,520	4,192,333	11.4
Dallas/Fort Worth, TX (Dallas/Fort Worth International)	DFW	28,378,761	31,708,943	11.7
San Antonio, TX (San Antonio International)	SAT	3,747,863	4,210,893	12.4
Orlando, FL (Orlando International)	MCO	16,773,111	18,890,286	12.6
Newark, NJ (Newark Liberty International)	EWR	16,551,713	18,761,904	13.4
San Diego, CA (San Diego International)	SAN	8,799,166	10,184,207	15.7
Atlanta, GA (Hartsfield-Jackson Atlanta International)	ATL	42,616,241	49,783,123	16.8
Baltimore, MD (Baltimore/Washington International Thurgood Marshall)	BWI	10,241,857	12,018,313	17.3
Nashville, TN (Nashville International)	BNA	4,972,039	5,933,579	19.3
Fort Lauderdale, FL (Fort Lauderdale-Hollywood International)	FLL	10,956,187	13,149,918	20.0
Portland, OR (Portland International)	PDX	6,905,934	8,379,061	21.3
Los Angeles, CA (Los Angeles International)	LAX	30,258,722	37,057,840	22.5
Boston, MA (Logan International)	BOS	13,231,132	16,366,187	23.7
Denver, CO (Denver International)	DEN	21,105,296	26,626,876	26.2
Chicago, IL (Chicago Midway International)	MDW	8,831,751	11,203,403	26.9
Washington, DC (Ronald Reagan Washington National)	DCA	8,738,789	11,292,497	29.2
New Orleans, LA (Louis Armstrong New Orleans International)	MSY	4,093,595	5,466,225	33.5
Houston, TX (William P Hobby)	HOU	4,571,909	6,285,558	37.5
New York, NY (John F. Kennedy International)	JFK	20,341,570	27,999,238	37.6
Seattle, WA (Seattle/Tacoma International)	SEA	14,665,517	20,223,367	37.9
Miami, FL (Miami International)	MIA	15,237,146	21,093,786	38.4
San Francisco, CA (San Francisco International)	SFO	16,412,266	24,374,805	48.5
Charlotte, NC (Charlotte Douglas International)	CLT	14,335,916	22,239,565	55.1
Austin, TX (Austin - Bergstrom International)	AUS	3,830,581	5,950,408	55.3
Dallas, TX (Dallas Love Field)	DAL	3,280,448	7,415,552	126.1
Top 50 U.S. Airports, total		607,582,270	685,768,816	12.9
All U.S. Airports		751,678,359	809,306,932	7.7

Figure A1. Changes in number of enplaned passengers in top 50 US airports (2005-2015)

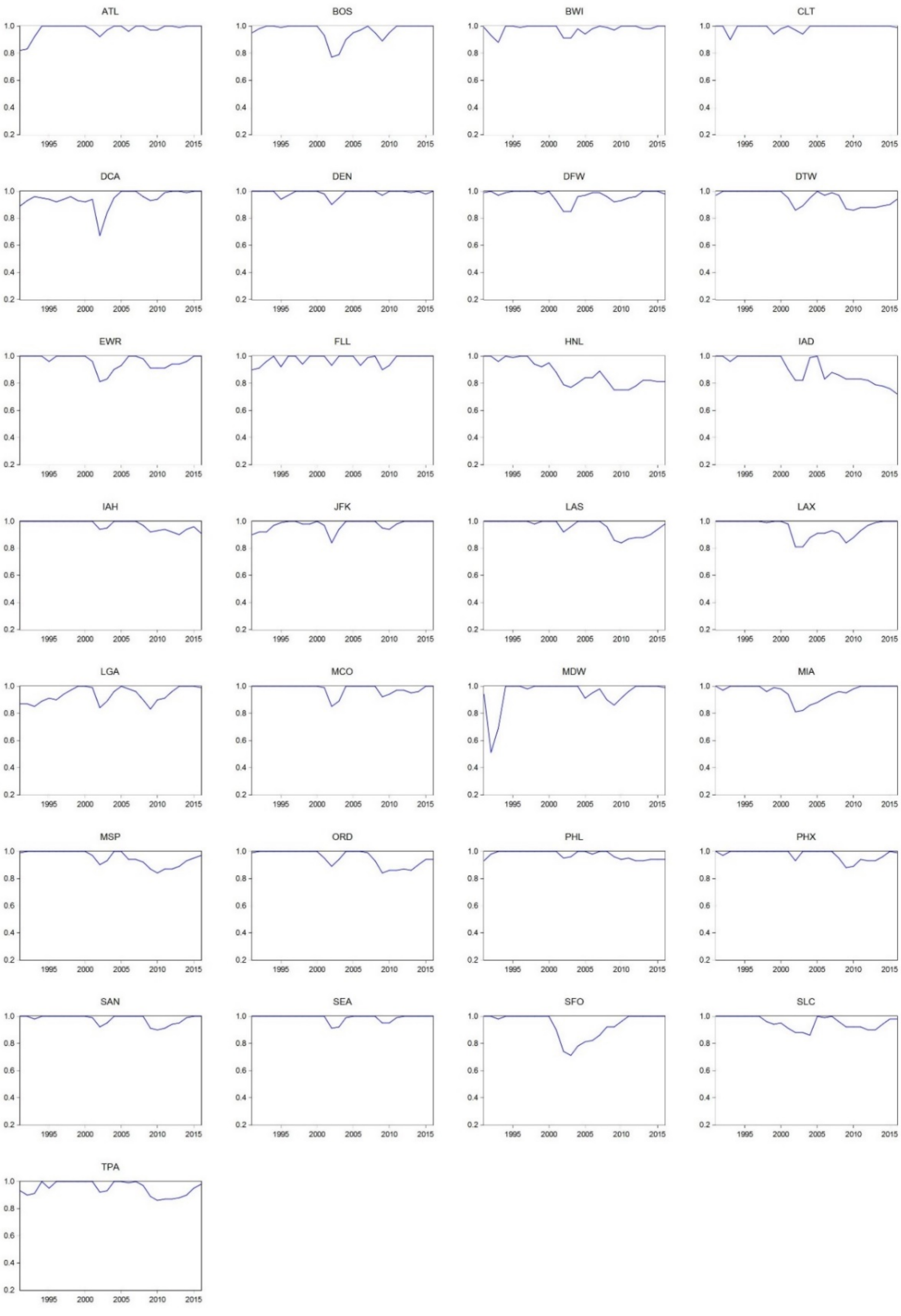

Figure A2. Proxy capacity utilization for large airports

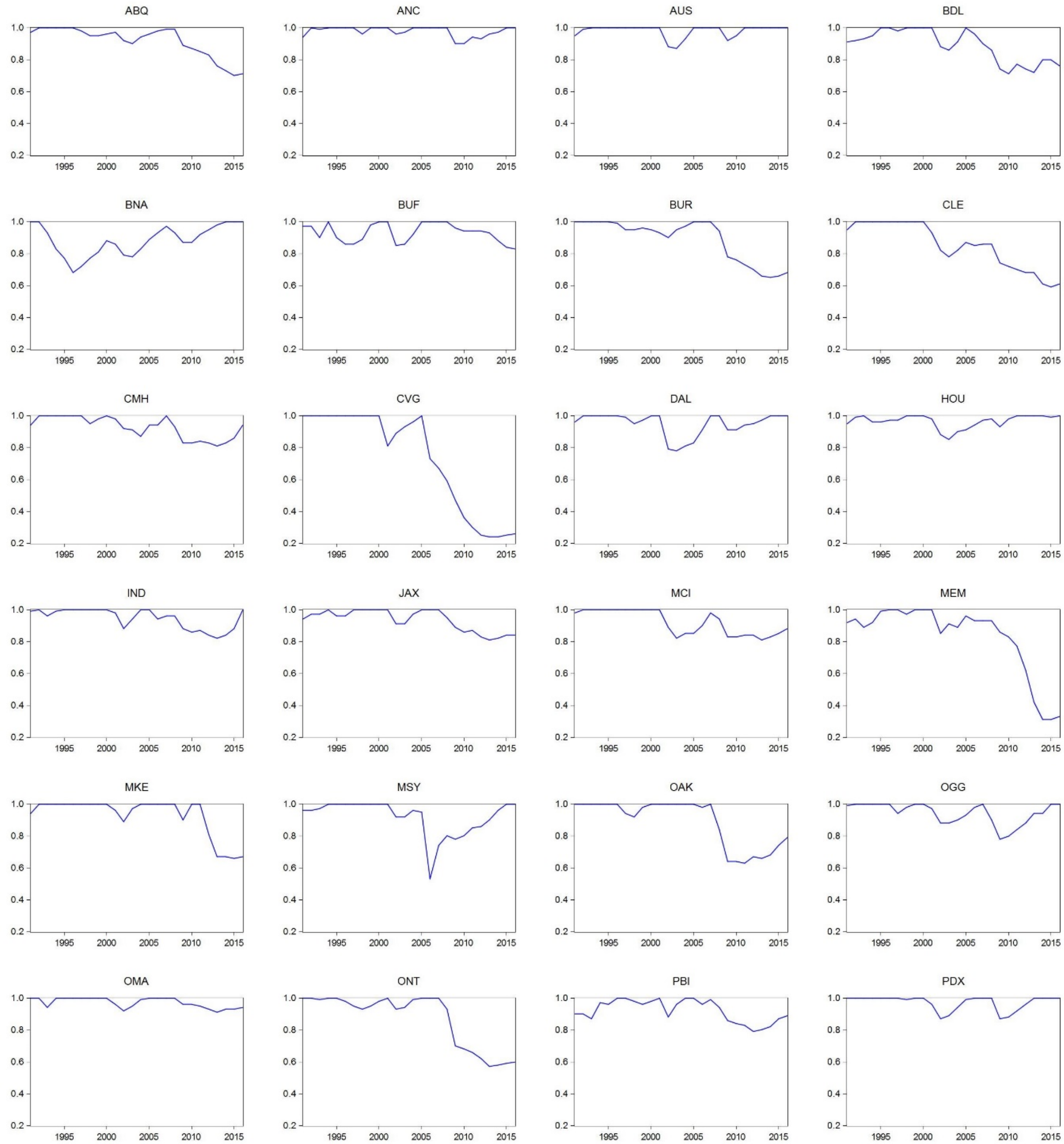

Figure A3. Proxy capacity utilization for medium airports (A-P)

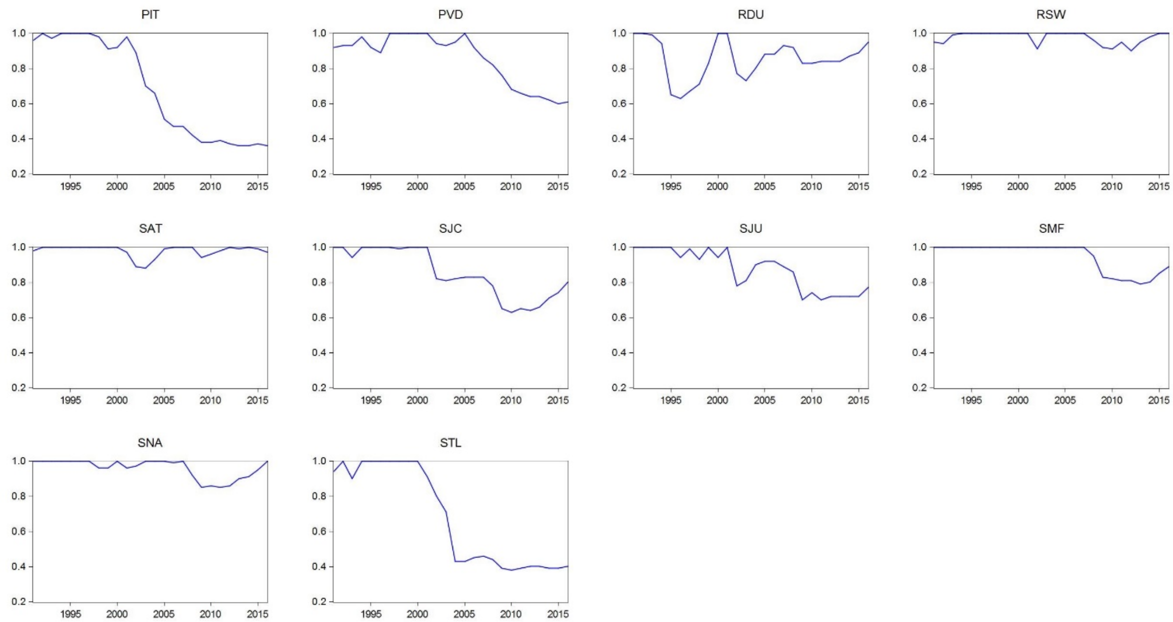

Figure A4. Proxy capacity utilization for medium airports (P-S)

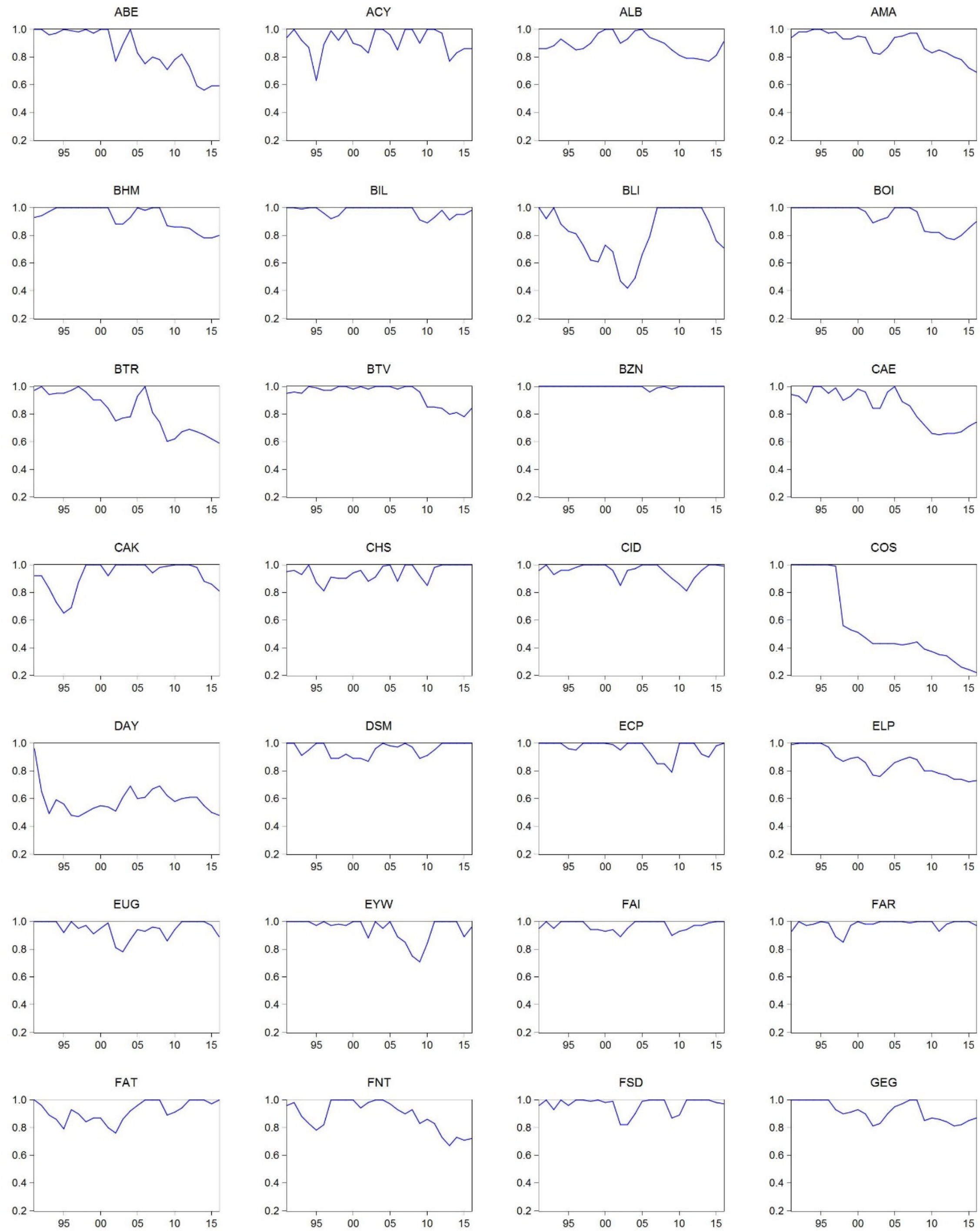

Figure A5. Proxy capacity utilization for small airports (A-G)

Figure A6. Proxy capacity utilization for small airports (G-O)

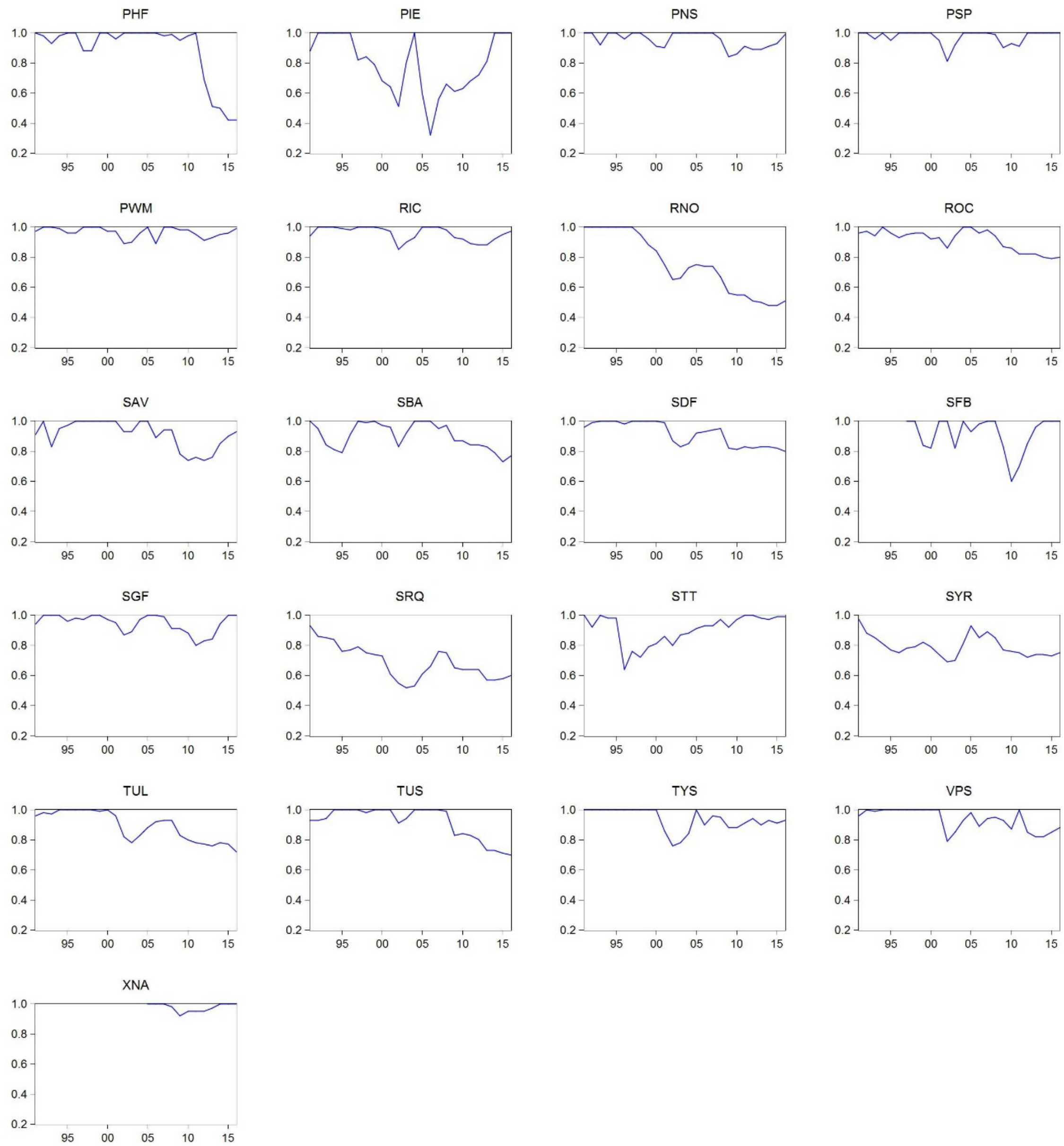

Figure A7. Proxy capacity utilization for small airports (P-X)

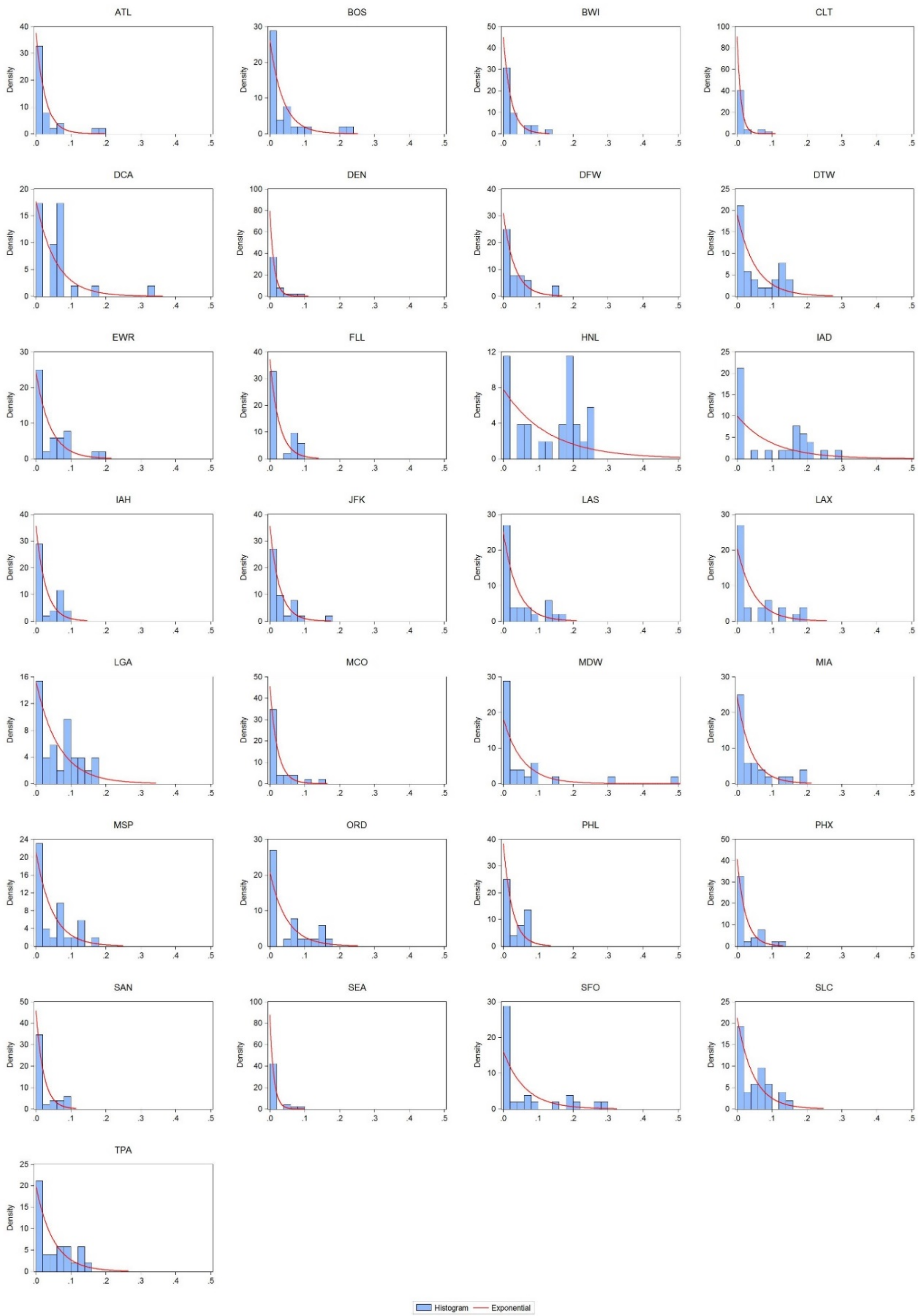

Figure A8. Proxy excess capacity for large airports

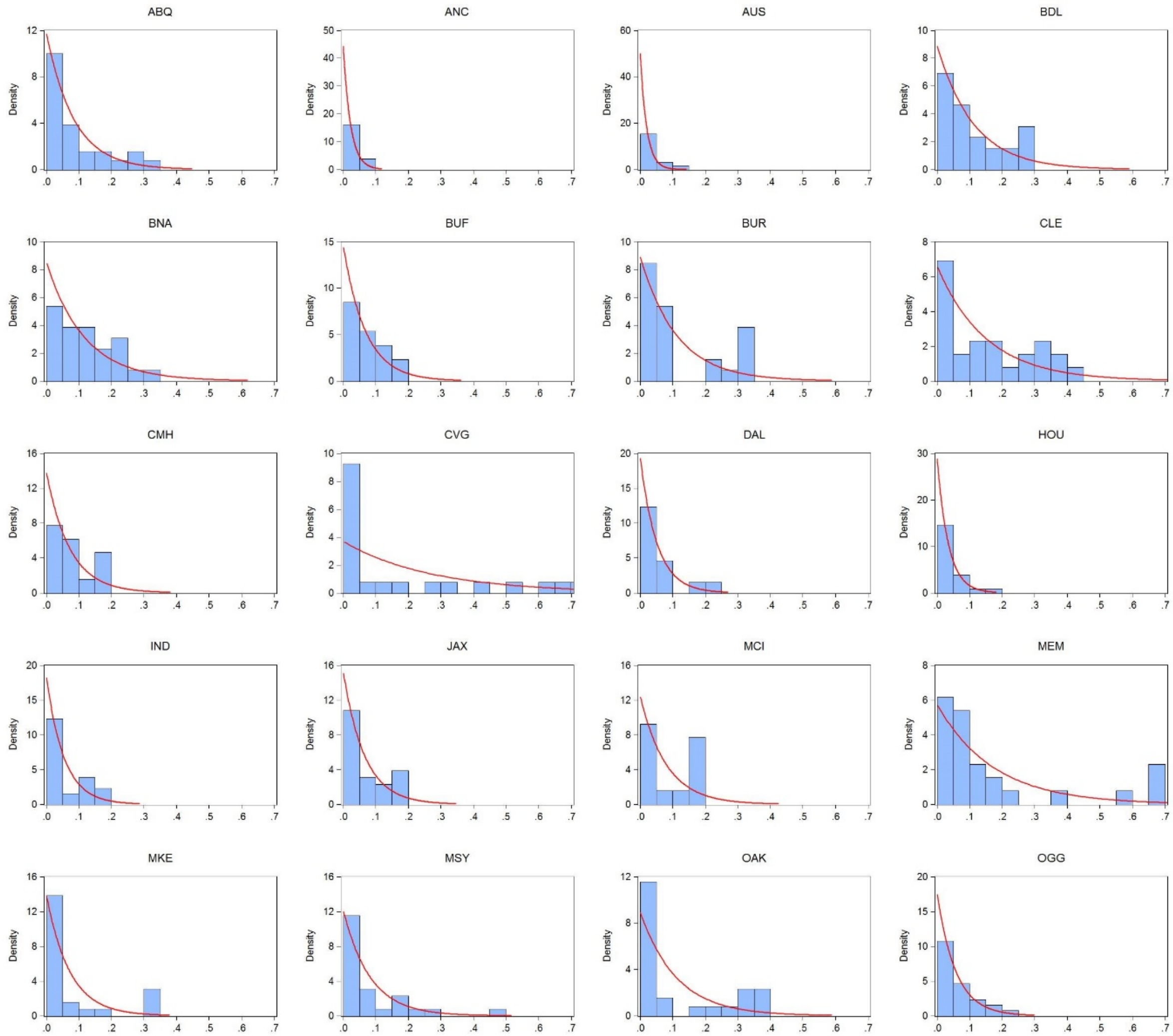

Figure A9. Proxy excess capacity for medium airports (A-O)

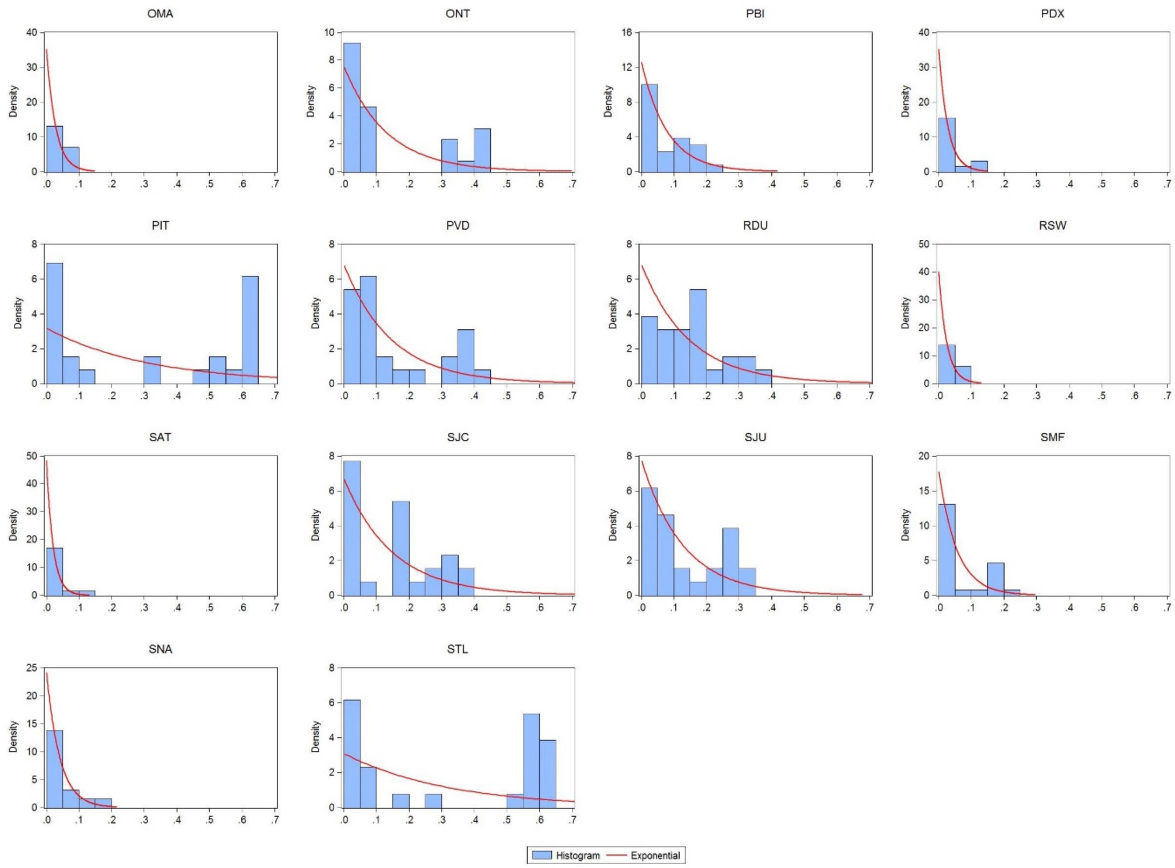

Figure A10. Proxy excess capacity for medium airports (O-S)

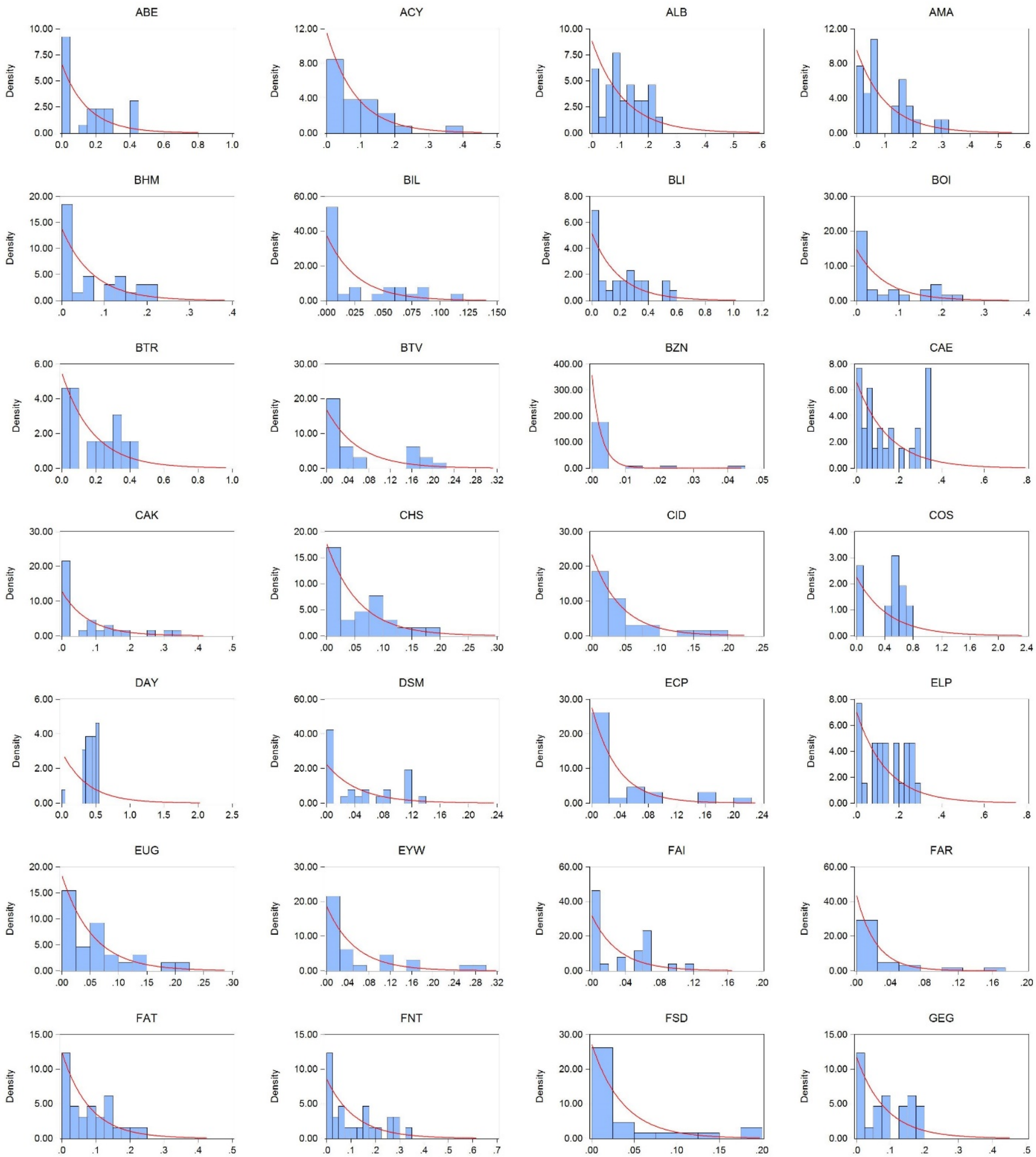

Figure A11. Proxy excess capacity for small airports (A-G)

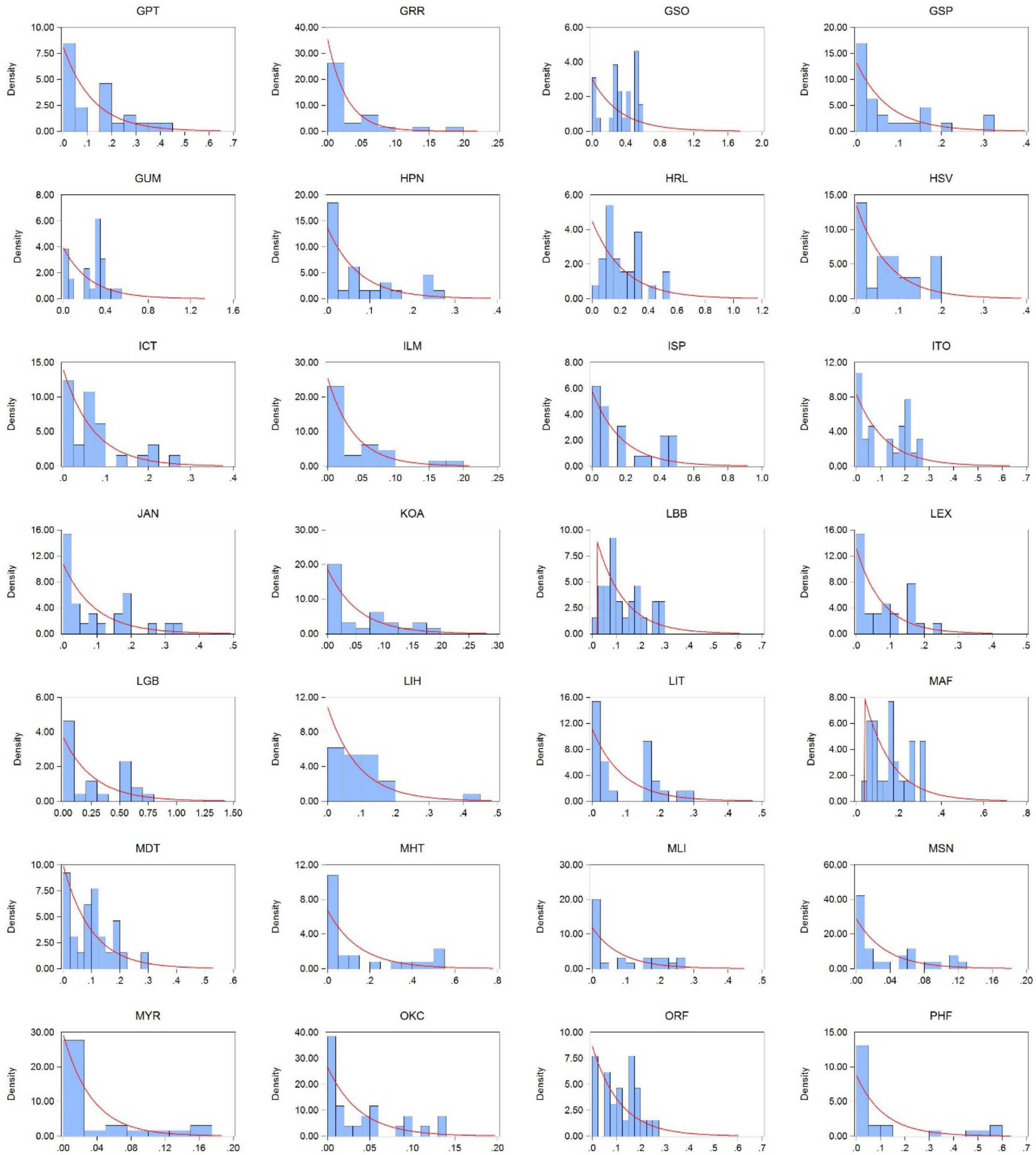

Figure A12. Proxy excess capacity for small airports (G-P)

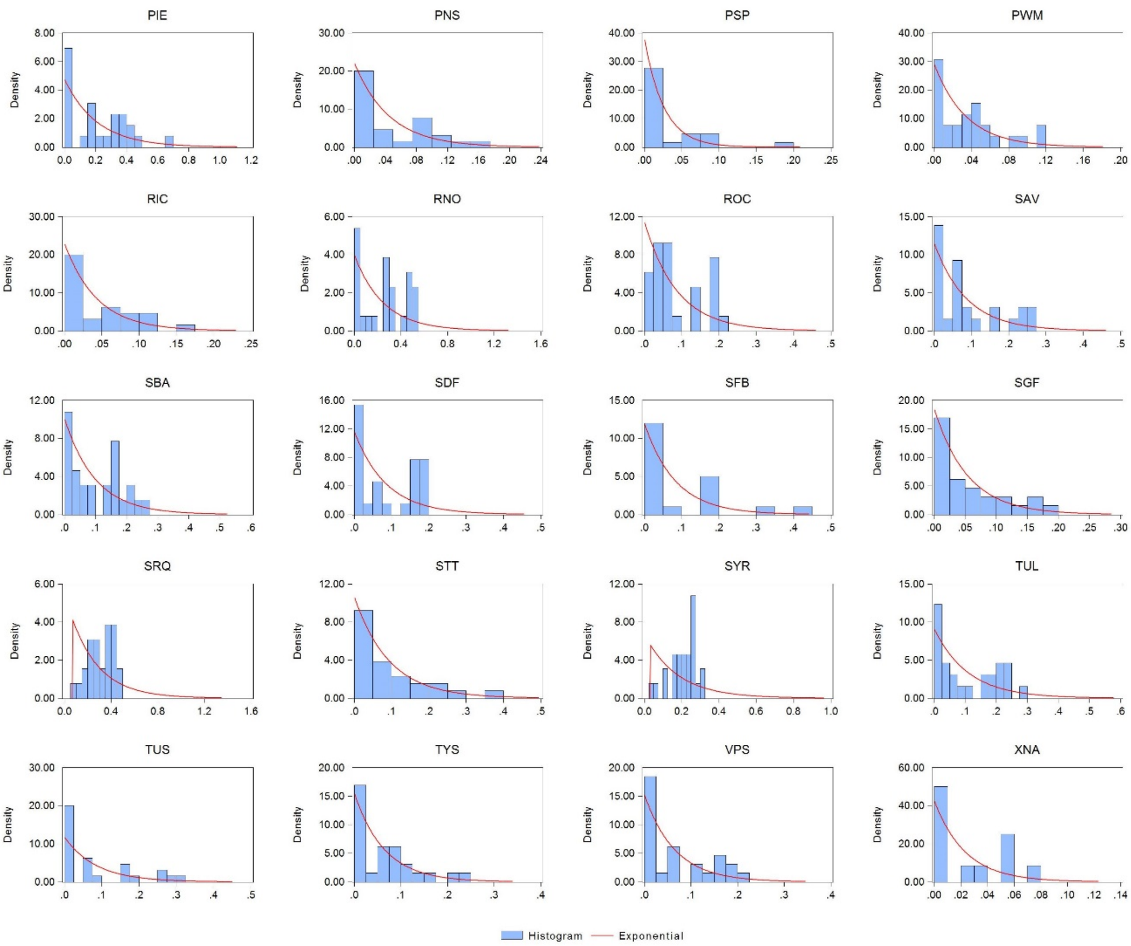

Figure A13. Proxy excess capacity for small airports (R-X)

Large

Airport	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
HNL	100%	100%	96%	100%	99%	100%	100%	94%	92%	95%	88%	79%	77%	80%	84%	84%	89%	82%	75%	75%	75%	78%	82%	82%	81%	81%
LGA	87%	87%	85%	89%	91%	90%	94%	97%	100%	100%	99%	84%	89%	96%	100%	98%	96%	90%	83%	90%	91%	96%	100%	100%	100%	99%
SAN	100%	100%	98%	100%	100%	100%	100%	100%	100%	100%	99%	92%	95%	100%	100%	100%	100%	100%	91%	90%	91%	94%	95%	99%	100%	100%
DCA	89%	93%	96%	95%	94%	92%	94%	96%	93%	92%	94%	67%	84%	95%	100%	100%	100%	96%	93%	94%	99%	100%	100%	99%	100%	100%
BOS	95%	98%	100%	100%	99%	100%	100%	100%	100%	100%	93%	77%	79%	90%	95%	97%	100%	95%	89%	95%	100%	100%	100%	100%	100%	100%
SLC	100%	100%	100%	100%	100%	100%	100%	96%	94%	95%	91%	88%	88%	86%	100%	99%	100%	96%	92%	92%	92%	90%	90%	94%	98%	98%
TPA	93%	90%	91%	100%	95%	100%	100%	100%	100%	100%	100%	92%	93%	100%	100%	99%	100%	97%	89%	86%	87%	87%	88%	90%	95%	98%
DFW	99%	100%	97%	99%	100%	100%	100%	100%	98%	100%	93%	85%	85%	96%	97%	99%	99%	96%	92%	93%	95%	96%	100%	100%	100%	98%
MIA	100%	97%	100%	100%	100%	100%	100%	96%	99%	98%	94%	81%	82%	86%	88%	91%	94%	96%	95%	98%	100%	100%	100%	100%	100%	100%
EWR	100%	100%	100%	100%	96%	100%	100%	100%	100%	100%	96%	81%	83%	90%	93%	100%	100%	98%	91%	91%	91%	94%	94%	96%	100%	100%
DTW	97%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	86%	89%	95%	100%	97%	99%	97%	87%	86%	88%	88%	88%	89%	90%	94%
BWI	99%	93%	88%	100%	100%	99%	100%	100%	100%	100%	100%	91%	91%	98%	94%	98%	100%	99%	97%	100%	100%	100%	98%	98%	100%	100%
ORD	99%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	89%	94%	100%	100%	100%	99%	93%	84%	86%	86%	87%	86%	90%	94%	94%
SFO	100%	100%	98%	100%	100%	100%	100%	100%	100%	100%	90%	74%	71%	78%	81%	82%	86%	92%	92%	96%	100%	100%	100%	100%	100%	100%
IAD	100%	100%	96%	100%	100%	100%	100%	100%	100%	100%	90%	82%	82%	99%	100%	83%	88%	86%	83%	83%	83%	82%	79%	78%	76%	72%
MSP	99%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97%	90%	93%	100%	100%	94%	94%	92%	87%	84%	87%	87%	89%	93%	95%	97%
MDW	94%	51%	69%	100%	100%	100%	98%	100%	100%	100%	100%	100%	100%	100%	91%	95%	98%	90%	86%	91%	96%	100%	100%	100%	100%	99%
FLL	90%	91%	96%	100%	92%	100%	100%	94%	100%	100%	100%	93%	100%	100%	100%	93%	99%	100%	90%	93%	100%	100%	100%	100%	100%	100%
PHL	93%	98%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	96%	100%	100%	98%	100%	100%	96%	94%	95%	93%	93%	94%	94%	94%
SEA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	91%	92%	99%	100%	100%	100%	100%	95%	95%	99%	100%	100%	100%	100%	100%
MCO	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	99%	85%	89%	100%	100%	100%	100%	100%	92%	94%	97%	97%	95%	96%	100%	100%
LAX	100%	100%	100%	100%	100%	100%	100%	99%	100%	100%	98%	81%	81%	88%	91%	91%	93%	91%	84%	88%	93%	97%	99%	100%	100%	100%
PHX	100%	97%	100%	100%	100%	100%	100%	100%	100%	100%	100%	93%	100%	100%	100%	100%	100%	95%	88%	89%	94%	93%	93%	96%	100%	99%
LAS	100%	100%	100%	100%	100%	100%	100%	98%	100%	100%	100%	92%	96%	100%	100%	100%	100%	96%	86%	84%	87%	88%	88%	90%	94%	98%
IAH	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	94%	95%	100%	100%	100%	100%	97%	92%	93%	94%	92%	90%	94%	96%	91%
CLT	100%	100%	90%	100%	100%	100%	100%	100%	94%	98%	100%	97%	94%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	99%
DEN	100%	100%	100%	100%	94%	97%	100%	100%	100%	100%	98%	90%	95%	100%	100%	100%	100%	100%	97%	100%	100%	100%	99%	100%	98%	100%
JFK	90%	92%	92%	97%	99%	100%	100%	98%	98%	100%	97%	84%	94%	100%	100%	100%	100%	100%	95%	94%	98%	100%	100%	100%	100%	100%
ATL	82%	83%	92%	100%	100%	100%	100%	100%	100%	100%	97%	92%	97%	100%	100%	96%	100%	100%	97%	97%	100%	100%	99%	100%	100%	100%

Medium

Airport	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
ABQ	97%	100%	100%	100%	100%	100%	98%	95%	95%	96%	97%	92%	90%	94%	96%	98%	99%	99%	89%	87%	85%	83%	76%	73%	70%	71%
ANC	94%	100%	99%	100%	100%	100%	100%	96%	100%	100%	100%	96%	97%	100%	100%	100%	100%	100%	90%	90%	94%	93%	96%	97%	100%	100%
AUS	95%	99%	100%	100%	100%	100%	100%	100%	100%	100%	100%	88%	87%	93%	100%	100%	100%	100%	92%	95%	100%	100%	100%	100%	100%	100%
BDL	91%	92%	93%	95%	100%	100%	98%	100%	100%	100%	100%	88%	86%	91%	100%	96%	90%	86%	74%	71%	77%	74%	72%	80%	80%	76%
BNA	100%	100%	93%	83%	77%	68%	72%	77%	81%	88%	86%	79%	78%	83%	89%	93%	97%	93%	87%	87%	92%	95%	98%	100%	100%	100%
BUF	97%	97%	90%	100%	90%	86%	86%	89%	98%	100%	100%	85%	86%	92%	100%	100%	100%	100%	96%	94%	94%	94%	93%	88%	84%	83%
BUR	100%	100%	100%	100%	100%	99%	95%	95%	96%	95%	93%	90%	95%	97%	100%	100%	100%	94%	78%	76%	73%	70%	66%	65%	66%	68%
CLE	95%	100%	100%	100%	100%	100%	100%	100%	100%	100%	93%	82%	78%	82%	87%	85%	86%	86%	74%	72%	70%	68%	68%	61%	59%	61%
CMH	94%	100%	100%	100%	100%	100%	100%	95%	98%	100%	98%	92%	91%	87%	94%	94%	100%	93%	83%	83%	84%	83%	81%	83%	86%	94%
CVG	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	81%	89%	93%	96%	100%	73%	67%	59%	47%	36%	30%	25%	24%	24%	25%	26%
DAL	96%	100%	100%	100%	100%	100%	99%	95%	97%	100%	100%	79%	78%	81%	83%	91%	100%	100%	91%	91%	94%	95%	97%	100%	100%	100%
HOU	95%	99%	100%	96%	96%	97%	97%	100%	100%	100%	98%	88%	85%	90%	91%	94%	97%	98%	93%	98%	100%	100%	100%	100%	99%	100%
IND	99%	100%	96%	99%	100%	100%	100%	100%	100%	100%	98%	88%	94%	100%	100%	94%	96%	96%	88%	86%	87%	84%	82%	84%	88%	100%
JAX	94%	97%	97%	100%	96%	96%	100%	100%	100%	100%	100%	91%	91%	97%	100%	100%	100%	95%	89%	86%	87%	83%	81%	82%	84%	84%
MCI	98%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	89%	82%	85%	85%	90%	98%	94%	83%	83%	84%	84%	81%	83%	85%	88%
MEM	92%	94%	89%	92%	99%	100%	100%	97%	100%	100%	100%	85%	91%	89%	96%	93%	93%	93%	86%	83%	77%	62%	42%	31%	31%	33%
MKE	94%	100%	100%	100%	100%	100%	100%	100%	100%	100%	96%	89%	97%	100%	100%	100%	100%	100%	90%	100%	100%	81%	67%	67%	66%	67%
MSY	96%	96%	97%	100%	100%	100%	100%	100%	100%	100%	100%	92%	92%	96%	95%	53%	74%	80%	78%	80%	85%	86%	90%	96%	100%	100%
OAK	100%	100%	100%	100%	100%	100%	94%	92%	98%	100%	100%	100%	100%	100%	100%	98%	100%	84%	64%	64%	63%	67%	66%	68%	74%	79%
OGG	99%	100%	100%	100%	100%	100%	94%	98%	100%	100%	97%	88%	88%	90%	93%	98%	100%	90%	78%	80%	84%	88%	94%	94%	100%	100%
OMA	100%	100%	94%	100%	100%	100%	100%	100%	100%	100%	96%	92%	95%	99%	100%	100%	100%	100%	96%	96%	95%	93%	91%	93%	93%	94%
ONT	100%	100%	99%	100%	100%	98%	95%	93%	95%	98%	100%	93%	94%	99%	100%	100%	100%	93%	70%	68%	66%	62%	57%	58%	59%	60%
PBI	90%	90%	87%	97%	96%	100%	100%	98%	96%	98%	100%	88%	96%	100%	100%	96%	99%	94%	86%	84%	83%	79%	80%	82%	87%	89%
PDX	100%	100%	100%	100%	100%	100%	100%	99%	100%	100%	96%	87%	89%	94%	99%	100%	100%	100%	87%	88%	92%	96%	100%	100%	100%	100%
PIT	96%	100%	97%	100%	100%	100%	100%	98%	91%	92%	98%	89%	70%	66%	51%	47%	47%	42%	38%	38%	39%	37%	36%	36%	37%	36%
PVD	92%	93%	93%	98%	92%	89%	100%	100%	100%	100%	100%	94%	93%	95%	100%	92%	86%	82%	76%	68%	66%	64%	64%	62%	60%	61%
RDU	100%	100%	99%	94%	65%	63%	67%	71%	83%	100%	100%	77%	73%	80%	88%	88%	93%	92%	83%	83%	84%	84%	84%	87%	89%	95%
RSW	95%	94%	99%	100%	100%	100%	100%	100%	100%	100%	100%	91%	100%	100%	100%	100%	100%	96%	92%	91%	95%	90%	95%	98%	100%	100%
SAT	98%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97%	89%	88%	93%	99%	100%	100%	100%	94%	96%	98%	100%	99%	100%	99%	97%
SJC	100%	100%	94%	100%	100%	100%	100%	99%	100%	100%	100%	82%	81%	82%	83%	83%	83%	78%	65%	63%	65%	64%	66%	71%	74%	80%
SJU	100%	100%	100%	100%	100%	94%	99%	93%	100%	94%	100%	78%	81%	90%	92%	92%	89%	86%	70%	74%	70%	72%	72%	72%	72%	77%
SMF	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	83%	82%	81%	81%	79%	80%	85%	89%
SNA	100%	100%	100%	100%	100%	100%	100%	96%	96%	100%	96%	97%	100%	100%	100%	99%	100%	92%	85%	86%	85%	86%	90%	91%	95%	100%
STL	94%	100%	90%	100%	100%	100%	100%	100%	100%	100%	91%	80%	71%	43%	43%	45%	46%	44%	39%	38%	39%	40%	40%	39%	39%	40%

Figure A14. Heat map of proxy capacity use at US airports (large and medium)

Small

Airport	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
ABE	100%	100%	96%	97%	100%	99%	98%	100%	97%	100%	100%	77%	89%	100%	83%	75%	80%	78%	71%	78%	82%	73%	59%	56%	59%	59%
ACY	94%	100%	92%	87%	63%	89%	99%	92%	100%	90%	88%	83%	100%	100%	96%	85%	100%	100%	90%	100%	100%	97%	77%	83%	86%	86%
ALB	86%	86%	88%	93%	89%	85%	86%	90%	97%	100%	100%	90%	93%	99%	100%	94%	92%	90%	85%	81%	79%	79%	78%	77%	81%	91%
AMA	94%	98%	98%	100%	100%	97%	98%	93%	93%	95%	94%	83%	82%	87%	94%	95%	97%	97%	86%	83%	85%	83%	80%	78%	72%	69%
BHM	93%	94%	97%	100%	100%	100%	100%	100%	100%	100%	100%	88%	88%	93%	100%	98%	100%	100%	87%	86%	86%	85%	81%	78%	78%	80%
BIL	100%	100%	99%	100%	100%	96%	92%	94%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	91%	89%	93%	98%	91%	95%	95%	98%
BLI	100%	92%	100%	88%	83%	81%	73%	62%	61%	73%	68%	47%	42%	49%	66%	79%	100%	100%	100%	100%	100%	100%	100%	90%	76%	71%
BOI	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97%	89%	91%	93%	100%	100%	100%	97%	83%	82%	82%	78%	77%	80%	85%	90%
BTR	97%	100%	94%	95%	95%	97%	100%	96%	90%	90%	84%	75%	77%	78%	93%	100%	81%	74%	60%	62%	67%	69%	67%	65%	62%	59%
BTV	95%	96%	95%	100%	99%	97%	97%	100%	100%	98%	100%	98%	100%	100%	100%	98%	100%	100%	96%	85%	85%	84%	80%	81%	78%	84%
BZN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	96%	99%	100%	98%	100%	100%	100%	100%	100%	100%	100%
CAE	94%	93%	88%	100%	100%	95%	99%	90%	93%	98%	96%	84%	84%	96%	100%	89%	86%	78%	72%	66%	65%	66%	66%	67%	71%	74%
CAK	92%	92%	83%	73%	65%	69%	87%	100%	100%	100%	92%	100%	100%	100%	100%	100%	94%	98%	99%	100%	100%	100%	98%	88%	86%	81%
CHS	95%	96%	93%	100%	87%	81%	91%	90%	90%	94%	96%	88%	91%	99%	100%	88%	100%	100%	92%	85%	98%	100%	100%	100%	100%	100%
CID	96%	100%	93%	96%	96%	98%	100%	100%	100%	100%	96%	85%	96%	97%	100%	100%	100%	95%	90%	86%	81%	90%	96%	100%	100%	99%
COS	100%	100%	100%	100%	100%	100%	99%	56%	53%	51%	47%	43%	43%	43%	43%	42%	43%	44%	39%	37%	35%	34%	30%	26%	24%	22%
DAY	96%	65%	49%	59%	56%	48%	47%	50%	53%	55%	54%	51%	61%	69%	60%	61%	67%	69%	62%	58%	60%	61%	61%	55%	50%	48%
DSM	100%	100%	91%	95%	100%	100%	89%	89%	92%	89%	89%	87%	96%	100%	98%	97%	100%	97%	89%	91%	95%	100%	100%	100%	100%	100%
ECP	100%	100%	100%	100%	96%	95%	100%	100%	100%	100%	99%	95%	100%	100%	100%	93%	85%	85%	79%	100%	100%	100%	92%	90%	98%	100%
ELP	99%	100%	100%	100%	100%	97%	90%	87%	89%	90%	86%	77%	76%	81%	86%	88%	90%	88%	80%	80%	78%	77%	74%	74%	72%	73%
EUG	100%	100%	100%	100%	92%	100%	95%	97%	91%	95%	99%	81%	78%	87%	94%	93%	96%	95%	86%	94%	100%	100%	100%	100%	97%	89%
EYW	100%	100%	100%	100%	97%	100%	97%	98%	97%	100%	100%	88%	100%	95%	100%	89%	85%	75%	71%	84%	100%	100%	100%	100%	89%	96%
FAI	95%	100%	95%	100%	100%	100%	100%	94%	94%	93%	94%	89%	95%	100%	100%	100%	100%	100%	90%	93%	94%	97%	97%	99%	100%	100%
FAR	93%	100%	97%	98%	100%	99%	89%	85%	97%	100%	98%	98%	100%	100%	100%	100%	99%	100%	100%	100%	93%	98%	100%	100%	100%	97%
FAT	100%	96%	89%	86%	79%	93%	90%	84%	87%	87%	80%	76%	86%	92%	96%	100%	100%	100%	89%	91%	94%	100%	100%	100%	97%	100%
FNT	96%	98%	88%	83%	78%	82%	100%	100%	100%	100%	94%	98%	100%	100%	97%	93%	90%	93%	83%	86%	83%	73%	67%	73%	71%	72%
FSD	96%	100%	93%	100%	96%	100%	100%	99%	100%	98%	99%	82%	82%	90%	99%	100%	100%	100%	87%	89%	100%	100%	100%	100%	98%	97%
GEG	100%	100%	100%	100%	100%	100%	93%	90%	91%	93%	90%	81%	83%	90%	95%	97%	100%	100%	85%	87%	86%	84%	81%	82%	85%	87%
GPT	98%	74%	99%	100%	83%	96%	100%	84%	100%	100%	91%	81%	98%	100%	93%	84%	99%	100%	85%	90%	83%	78%	75%	69%	64%	58%
GRR	95%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97%	100%	100%	100%	92%	93%	87%	80%	95%	100%	93%	96%	100%	100%	100%
GSO	93%	99%	100%	100%	100%	78%	59%	66%	73%	73%	75%	66%	68%	71%	73%	61%	58%	58%	48%	45%	48%	48%	46%	46%	45%	46%
GSP	92%	93%	97%	100%	98%	97%	100%	96%	100%	100%	97%	85%	87%	93%	100%	84%	83%	79%	69%	69%	88%	100%	98%	100%	100%	100%
GUM	93%	100%	94%	99%	100%	100%	100%	78%	70%	77%	77%	60%	48%	62%	65%	67%	66%	63%	55%	62%	63%	70%	70%	67%	67%	72%
HPN	100%	94%	100%	100%	100%	100%	100%	92%	99%	97%	93%	87%	84%	87%	93%	89%	100%	100%	100%	100%	98%	94%	77%	74%	76%	77%
HRL	89%	93%	100%	94%	93%	87%	87%	87%	87%	87%	86%	71%	73%	79%	80%	80%	82%	78%	70%	67%	67%	69%	66%	57%	50%	46%
HSV	94%	100%	97%	89%	87%	90%	100%	100%	100%	100%	94%	87%	94%	100%	100%	89%	92%	98%	91%	92%	98%	94%	80%	82%	81%	80%
ICT	96%	100%	99%	94%	100%	100%	94%	87%	82%	79%	75%	78%	92%	99%	98%	95%	100%	100%	92%	94%	93%	92%	91%	95%	96%	94%
ILM	100%	100%	93%	100%	91%	90%	94%	100%	100%	100%	99%	85%	81%	100%	100%	92%	100%	100%	97%	98%	98%	98%	97%	93%	93%	100%
ISP	100%	97%	93%	100%	94%	100%	93%	59%	100%	100%	91%	82%	83%	85%	90%	98%	100%	92%	81%	74%	68%	60%	55%	56%	51%	51%
ITO	100%	100%	94%	100%	100%	100%	100%	96%	93%	96%	93%	86%	77%	75%	80%	84%	100%	87%	80%	78%	75%	79%	81%	78%	79%	78%
IWA																88%	100%	100%	100%	100%	100%	100%	100%	86%	88%	91%
JAN	97%	100%	99%	96%	97%	100%	100%	100%	100%	100%	99%	85%	89%	92%	100%	100%	95%	92%	85%	82%	81%	81%	80%	73%	67%	69%
KOA	100%	96%	100%	99%	100%	100%	100%	100%	100%	100%	95%	87%	88%	91%	98%	100%	100%	90%	83%	82%	85%	88%	92%	91%	97%	100%
LBB	92%	93%	96%	98%	95%	97%	96%	92%	91%	93%	89%	81%	81%	85%	88%	90%	92%	92%	86%	83%	81%	78%	73%	72%	71%	74%
LEX	98%	100%	99%	93%	94%	100%	100%	100%	97%	92%	85%	80%	100%	100%	90%	84%	85%	83%	76%	85%	89%	90%	88%	96%	99%	100%
LGB	100%	63%	44%	37%	26%	31%	42%	44%	48%	49%	40%	71%	100%	100%	100%	92%	94%	94%	95%	96%	100%	100%	91%	87%	78%	77%
LIH	99%	98%	60%	88%	91%	97%	95%	100%	100%	100%	96%	89%	87%	87%	88%	92%	100%	94%	84%	82%	83%	88%	92%	91%	93%	89%
LIT	98%	100%	100%	100%	100%	99%	99%	99%	100%	100%	97%	85%	82%	85%	96%	96%	96%	93%	85%	85%	82%	85%	83%	78%	73%	72%
MAF	93%	90%	93%	93%	96%	93%	90%	88%	83%	81%	77%	68%	68%	69%	75%	79%	83%	84%	74%	73%	80%	84%	85%	91%	92%	86%
MDT	97%	100%	100%	100%	96%	86%	100%	100%	99%	90%	80%	82%	89%	93%	92%	79%	86%	88%	84%	88%	90%	90%	89%	88%	82%	72%
MHT	100%	97%	94%	100%	98%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	92%	88%	88%	76%	65%	63%	58%	55%	49%	47%	47%
MLI	100%	100%	85%	84%	75%	82%	89%	100%	100%	100%	100%	92%	100%	100%	100%	100%	100%	100%	96%	98%	90%	82%	79%	78%	76%	75%
MSN	89%	100%	100%	95%	94%	100%	100%	100%	100%	97%	100%	100%	100%	100%	99%	95%	94%	88%	90%	91%	89%	93%	98%	99%	99%	100%
MYR	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	98%	83%	83%	100%	100%	88%	99%	93%	90%	97%	100%	87%	94%	100%	100%	100%
OKC	96%	99%	98%	100%	100%	100%	100%	99%	100%	100%	99%	87%	90%	96%	100%	100%	100%	100%	89%	90%	91%	95%	95%	97%	95%	87%
ORF	93%	94%	92%	100%	84%	82%	85%	84%	88%	89%	88%	99%	100%	100%	100%	94%	95%	90%	86%	84%	81%	82%	79%	76%	74%	85%
PHF	100%	98%	93%	98%	100%	100%	88%	88%	100%	100%	96%	100%	100%	100%	100%	100%	98%	99%	95%	98%	100%	69%	51%	50%	42%	42%
PIE	88%	100%	100%	100%	100%	100%	82%	84%	79%	68%	64%	51%	80%	100%	60%	32%	56%	66%	61%	63%	68%	72%	81%	100%	100%	100%
PNS	100%	100%	92%	100%	100%	96%	100%	100%	96%	91%	90%	100%	100%	100%	100%	100%	100%	96%	84%	86%	91%	89%	89%	91%	93%	99%
PSP	100%	100%	96%	100%	95%	100%	100%	100%	100%	100%	95%	81%	92%	100%	100%	100%	100%	99%	90%	93%	91%	100%	100%	100%	100%	100%
PWM	97%	100%	100%	99%	96%	96%	100%	100%	100%	97%	97%	89%	90%	96%	100%	89%	100%	100%	98%	98%	95%	91%	93%	95%	96%	99%
RIC	94%	100%	100%	100%	99%	98%	100%	100%	100%	99%	97%	85%	90%	93%	100%	100%	100%	98%	93%	92%	89%	88%	88%	92%	95%	97%
RNO	100%	100%	100%	100%	100%	100%	100%	95%	88%	84%	75%	65%	66%	73%	75%	74%	74%	67%	56%	55%	55%	51%	50%	48%	48%	51%
ROC	96%	97%	94%	100%	96%	93%	95%	96%	96%	92%	93%	86%	94%	100%	100%	96%	98%	94%	87%	86%	82%	82%	82%	80%	79%	80%
SAV	91%	100%	83%	95%	97%	100%	100%	100%	100%	100%	100%	93%	93%	100%	100%	89%	94%	94%	78%	74%	76%	74%	76%	85%	90%	93%
SBA	100%	95%	84%	81%	79%	91%	100%	99%	100%	97%	96%	83%	92%	100%	100%	100%	95%	97%	87%	87%	84%	84%	83%	79%	73%	77%
SDF	96%	99%	100%	100%	100%	98%	100%	100%	100%	100%	99%	87%	83%	85%	92%	93%	94%	95%	82%	81%	83%	82%	83%	83%	82%	80%
SFB							100%	100%	84%	82%	100%	100%	82%	100%	93%	98%	100%	100%	83%	60%	70%	85%	96%	100%	100%	100%
SGF	94%	100%	100%	100%	96%	98%	97%	100%	100%	97%	95%	87%	89%	97%	100%	100%	99%	91%	91%	88%	80%	83%	84%	94%	100%	100%
SRQ	93%	86%	85%	84%	76%	77%	79%	75%	74%	73%	61%	55%	52%	53%	61%	66%	76%	75%	65%	64%	64%	64%	57%	57%	58%	60%
STT	100%	92%	100%	98%	98%	64%	76%	72%	79%	81%	86%	80%	87%	88%	91%	93%	93%	97%	92%	97%	100%	100%	98%	97%	99%	99%
SYR	97%	88%	85%	81%	77%	75%	78%	79%	82%	79%	74%	69%	70%	81%	93%	85%	89%	85%	77%	76%	75%	72%	74%	74%	73%	75%
TUL	96%	98%	97%	100%	100%	100%	100%	100%	99%	100%	96%	82%	78%	83%	88%	92%	93%	93%	83%	80%	78%	77%	76%	78%	77%	72%
TUS	93%	93%	94%	100%	100%	100%	100%	98%	100%	100%	100%	91%	94%	100%	100%	100%	100%	99%	83%	84%	83%	80%	73%	73%	71%	70%
TYS	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	86%	76%	78%	84%	100%	90%	96%	95%	88%	88%	91%	94%	90%	93%	91%	93%
VPS	96%	100%	99%	100%	100%	100%	100%	100%	100%	100%	100%	79%	85%	93%	98%	89%	94%	95%	93%	87%	100%	85%	82%	82%	85%	88%
XNA															100%	100%	100%	98%	92%	95%	95%	95%	97%	100%	100%	100%

Figure A15. Heat map of proxy capacity use at US airports (small)

Table A4. First order autocorrelations for capacity utilization levels by airport size (large and medium)

Airport	Autocorrelation	Airport	Autocorrelation
	Large		**Medium**
SFO	0.90	**PIT**	0.97
HNL	0.89	**STL**	0.97
MSP	0.86	**SMF**	0.96
ORD	0.85	**CVG**	0.95
MIA	0.84	**OAK**	0.94
LAS	0.84	**SJC**	0.94
DTW	0.81	**PVD**	0.93
LAX	0.77	**CLE**	0.93
IAD	0.76	**BUR**	0.93
TPA	0.73	**ONT**	0.92
IAH	0.72	**MEM**	0.89
BOS	0.71	**ABQ**	0.88
SLC	0.70	**BDL**	0.88
PHL	0.70	**JAX**	0.88
EWR	0.69	**MCI**	0.87
DFW	0.67	**SNA**	0.85
SAN	0.67	**CMH**	0.84
PHX	0.66	**BNA**	0.83
LGA	0.64	**SJU**	0.83
ATL	0.61	**MKE**	0.82
SEA	0.48	**PBI**	0.80
MDW	0.47	**OGG**	0.76
JFK	0.46	**IND**	0.76
DCA	0.45	**DAL**	0.72
MCO	0.44	**HOU**	0.71
BWI	0.33	**SAT**	0.68
DEN	0.33	**OMA**	0.68
FLL	0.12	**PDX**	0.66
CLT	0.00	**MSY**	0.62
		RDU	0.62
		AUS	0.55
		ANC	0.54
		BUF	0.52
		RSW	0.50
Mean	**0.62**		**0.84**
SD	**0.23**		**0.10**

Table A5. First order autocorrelations for capacity utilization levels by airport size (small)

Airport	Autocorrelation Small	Airport	Autocorrelation Small
RNO	0.95	**GSP**	0.74
MHT	0.93	**RIC**	0.72
COS	0.91	**SBA**	0.71
LBB	0.90	**ISP**	0.70
BTV	0.90	**PIE**	0.69
BOI	0.90	**FAT**	0.68
GSO	0.90	**TYS**	0.68
CAE	0.89	**EYW**	0.65
LGB	0.89	**STT**	0.64
ELP	0.89	**LEX**	0.64
GUM	0.88	**SYR**	0.63
TUL	0.87	**XNA**	0.63
MAF	0.87	**CID**	0.61
BLI	0.87	**MSN**	0.60
TUS	0.86	**PNS**	0.60
SDF	0.85	**BIL**	0.59
BTR	0.85	**GRR**	0.59
JAN	0.85	**HSV**	0.57
HRL	0.84	**MDT**	0.56
BHM	0.84	**VPS**	0.55
ALB	0.83	**DSM**	0.55
LIT	0.83	**ECP**	0.52
FNT	0.83	**OKC**	0.50
ROC	0.82	**SFB**	0.50
SRQ	0.82	**EUG**	0.48
PHF	0.82	**FAI**	0.47
ABE	0.82	**FSD**	0.46
CAK	0.81	**GPT**	0.44
ITO	0.81	**IWA**	0.43
AMA	0.80	**PSP**	0.39
ICT	0.79	**FAR**	0.38
GEG	0.79	**DAY**	0.35
MLI	0.78	**CHS**	0.30
KOA	0.78	**PWM**	0.29
ORF	0.78	**MYR**	0.28
HPN	0.75	**ACY**	0.25
SAV	0.75	**LIH**	0.23
SGF	0.74	**ILM**	0.21
		BZN	0.11
Mean	**0.83**		**0.48**
SD	**0.04**		**0.15**