ORGANIZATIONAL DESIGN MAKES A DIFFERENCE: THE IMPACT OF OPERATIONAL CONTROL ON THE FINANCIAL PERFORMANCE OF SMALL BUSINESSES

By

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TABLE OF CONTENTS

INDEX OF TABLES AND FIGURES

ORGANIZATIONAL DESIGN MAKES A DIFFERENCE: THE IMPACT OF OPERATIONAL CONTROL ON THE FINANCIAL PERFORMANCE OF SMALL BUSINESSES

ABSTRACT

Organizational design is the art of devising structures which enable teams to attain their strategic goals. Despite decades of efforts, specific "hands-on" recommendations for "good fitting" management structures have been rare and even conflicting (Nadler & Tushman, 1997; Rivkin & Siggelkow, 2003). This study is an early step in resolving that conundrum with specific, actionable recommendations for optimal organizational design. Building on the dual constructs of *agency theory* and *ineffectual principals*, this study quantifies the "fit" of the organizational structure with the new construct of "*operational control.*" This paper adds to the literature of organizational design by directly linking the "fit" of the organization to the economic success of the firm. This research also eliminates some of the confounds found in other studies by limiting the sample to just one group of highly similar small businesses, within one industry, one geography, and one point in time: general aviation airports in Florida in 2019. The results then are validated with a large hold-out sample. The study found that 116 of the 235 airports in the combined sample suffered from a poorly-fitting "multi-function" design which stunted the economic performance of those airports by approximately $20.4 million per airport. This finding suggests that approximately 1,700 small airports across the United States suffer from poor managerial fit which, if remedied, could release $34 billion in enhanced economic activity into the communities they serve.

CHAPTER 1. INTRODUCTION

Organizational design is the art of devising structures which enable firms to attain strategic goals which, in commerce, usually means profits (Baligh, Burton & Obel, 1996). Over nearly a century, scholars have produced a large library of research to attempt to understand organizations, define optimal structures, predict successes, and explain failures (Khandwalla, 1973; Covin, & Slevin, 1988; Ambrose & Schminke, 2003; Olson, Slater & Hult, 2005; among others). Indeed, even Adam Smith's ground-breaking opus "The Wealth of Nations" (1776) recommended a very specific and surprisingly modern organizational design: the division of labor into smaller tasks. Most modern research focuses on publicly traded companies making billion-dollar decisions, but the industries have been diverse, the samples sizes have been small, the findings sometimes contradictory, and actionable recommendations for general business practitioners are rare. This has caused some researchers to ask if organizational design even matters (Pugh, Hickson, Hinings & Turner, 1968; Nadler & Tushman, 1997; Rivkin & Siggelkow, 2003; Liozu, Hinterhuber & Somers, 2014). There also is a large body of research touching on the differences between for-profit organizations and public service agencies and bureaus (e.g., Arambula, 2008; Bryson, Ackermann & Eden, 2007; Curristine, Lonti & Joumard, 2007; Perry & Rainey, 1988; Alonso & Lewis, 2001)

Does Organizational Design Matter?

Does the design of an organization effect its performance? Does the "org chart" actually matter when one mostly cares about performance and profits? For decades, researchers have attempted to discern predictors of organizational success, trying to learn how and why some organizations outperform others. Most researchers would agree that performance is determined, at least in part, by the quality of a firm's strategy and the efficiency with which that strategy is implemented, and success rarely hinges on one single decision or factor (Lenz, 1980; Olson, Slater & Hult, 2005). While some research has demonstrated that organizational structure affects organizational performance (Covin & Slevin, 1989; Jennings & Seaman, 1990; Ambrose & Schminke, 2003; Colombo, Delmastro & Rabbiosi, 2012) few studies have drawn a clear connection linking the organizational chart to the bottom line (Carzo Jr. & Yanouzas, 1969). Additionally, a few studies have suggested the construct of equifinality may be the most relevant explanation, which holds that organizational design matters less than the quality of the implementation of whichever strategy has been selected (Katz & Kahn, 1978; Venkatraman, 1990). But it is logical that organizational design could be a favorite tool for managers because it is one of the few operational decisions which can be implemented quickly, easily, and internally, generally without reference to suppliers, competitors, customers, or other stakeholders. It allows managers to be responsive as plans evolve, as each strategic change imposes "different administrative requirements which are resolved by different forms of internal organization" (White, 1986, p. 220). On paper, at least, organizational design seems of paramount importance.

If organizational design is important, related questions must be considered. How does one define an "effective" organizational design? What are the circumstances under which one design outperforms another? Are any contextual factors — such as resource availability, organization size, production technology, competitive responses, or the skills of the executives — important? Are all contextual factors equally relevant (Pugh et al., 1963; Khandwalla, 1973)? Perhaps organizational design is not the principal independent driver of organizational success but a moderator, changing its impact under different conditions (Covin & Slevin, 1988; Ambrose & Schminke, 2003).

This study attempts to resolve one crucial aspect of organizational design, which is the link between the organization's structure and the successful fulfillment of an organization's long-term objectives. This paper expands the literature of organizational design with a research effort which controls many of the confounding variables which have troubled earlier researchers. Instead of giant organizations, this study looks at small ones. Instead of diverse industries, it looks at just one. Instead of using proprietary business processes, these organizations use very similar procedures and equipment, as defined by the Federal Aviation Administration (FAA). Instead of multiple regions or periods, it is limited to one state and one point in time.

This research asserts that the "fit" of the organizational design can be measured by the degree of *operational control* granted to management to run the enterprise free from interference from the legal owners of the firm. This analysis compares the degree of *operational control* of selected small airports to the *economic impact* each airport produces for their community. This methodology could be generalized as an examination of the link between the managerial structure of an organization and the financial outcomes of that firm. Ultimately, this study seeks to answer a simple question: all other factors being equal, is there a managerial design which enables organizations to better achieve their goals? Or, to ask the question in the obverse, is it possible to quantify the deleterious effects of an ill-fitting organizational structure?

However, potentially there are significant operational pitfalls in this analysis. Most critically, the strength and direction of the hypothesized relationship is shrouded by noisy, incomplete and/or inconsistent airport data. In fact, the performance of these small general aviation ("GA") airports has been such a mystery that it is commonplace across the industry to assert that "if you've seen one general aviation airport, you've just seen one aviation airport." It is felt that GA airports are all so different, so uniquely reflective of their history, their geography, their populations and local economies, and unique circumstances that it is virtually impossible to develop even a basic "rule of thumb" which might distinguish successful airports from unsuccessful ones. This author rejects that assertion. It is implausible that airports (or any organization) could succeed or fail purely by luck or by the grace of their geography. The literature on organizational design, years of executive experience, and decades of aeronautical activities has convinced this researcher that there must be "a knob to turn" which can direct and amplify the desired organizational outcomes, however subtle or obscure that knob may be.

Background: General Aviation

Building on the work of Olson, Slater and Hult (2005), this econometric analysis will be very narrowly defined: a non-random subset of the 20,002 public-use general aviation airports in the United States. General aviation (GA) is a broad term describing all civilian aviation operations that are neither traditional airline services nor military activities (Canada, 2017[1]; United Kingdom, 2018). The most common GA activities include flying privately-owned airplanes, corporate aviation, charter trips and/or "fractional ownership", public safety flights including police, air ambulance and firefighting, agricultural aviation (crop dusting and

[1] As noted elsewhere in this report, 42 different airport economic impact studies were collected for this research. All of them are listed in the References and further reviewed in Appendix 1, with annotations. These studies were produced by government agencies and/or contractors and are not peer-reviewed. For the purposes of clarity and brevity, when referenced in this report those studies simply will be identified by geography and year (e.g., "Canada, 2017").

such), aerial surveys and photography, and flight training. According to recent estimates by the International Council of Aircraft Owner and Pilot Associations (IAOPA), there are more than 350,000 aircraft and 700,000 pilots worldwide who participate in the global GA community. In comparison, commercial aviation accounts for 60,000 aircraft (only 15% of the global total) and 400,000 pilots (36% of the total), although admittedly the commercial aviation airplanes are much larger, fly more frequently and carry more people (Canada, 2017). Nonetheless, general aviation is a large and robust business, world-wide.

Every airplane needs an airport. As shown in Table 1, there are three general categories of ownership of the airports in the U.S.: military airfields, privately-owned airports, and civilian airports owned by towns, cities, counties, states, or the Federal government. For the purposes of this study, military airports and the largest civil airports will be excluded, as will be explained in detail below. Speaking most generally, however, the operations, motivations, and key performance indicators used at military airports are very different from a normal commercial business and would not fit this econometric analysis. Similarly, commercial airports characterized as “large” or “medium” hubs by the FAA are excluded from this study because they are quasi-private enterprises and have professional managers, large and independent budgets, employ sophisticated engineering teams and complex information systems, all of which are generally unavailable to smaller airports. In an econometric study of this type, the data from either of these types of airports would appear as outliers and would overwhelm the variance in the data of the smaller airports.[2]

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[2] There are two other airport governance models, “privatized” airports and “unmanaged” airports. The author can find no public airports in the U.S. which have been privatized, but that is an operational model in the UK, Canada and Europe. Additionally, airports can be completely unmanaged, with no services, security, fuel or fees. These usually are found in wilderness areas or national parks. These types of facilities are outside the parameters of this study and are mentioned here merely for the sake of completeness.

Table 1:

The Number and Ownership of FAA Registered Airports in the U.S.

Ownership	# Fields
Military (All)	313
Privately-Owned Fields	14,728
Public-Owned Fields	4,961
Total, All Airports	20,002

Focusing on the thousands of smaller airports, it's important to acknowledge that these are businesses, and in many cases ferociously competitive ones. Airports compete among each other to attract airlines, charter flights, plus privately-owned Cessnas and Pipers. Airports compete to sell fuel to their pilots, rent hangars to their owners, train at their flight schools, and visit their repair shops. Airports also compete for local enterprises such as hotels and restaurants to be based at their facilities. The economic contribution to their local communities of the 493 largest airports in the country — those with commercial airline service — is estimated to be $1.406 trillion; industry experts estimate the cumulative economic impact for the smaller airports (those without commercial airline service) to be about 10% of the larger airports, or in the range of $100-$150 billion annually (Airports Council International, 2017; ITRE, 2019).

While many airports are economic deserts, devoid of traffic and bereft of economic activity, some airports prosper and attract both flyers and businesses. Under-performing airports are a lost opportunity for economic growth and well-being. One possible explanation for suboptimal results is an inappropriate organizational configuration, which is to say, there could be a poor "fit" between the airport's management team and the airport's operational goals (Powell, 1992; Yeung et al., 2002). As noted by White (1986, p. 220), "The logic linking business performance to its internal organization is compelling." Indeed, while there may be many possible structures to use when effectively managing an organization — each one appropriate to a specific set of circumstances (Khandwalla, 1973) — since all airports deal with the same basic circumstances, technologies, and procedures, it is highly plausible there is but one optimal organizational design for small airports. However, given the inconsistent performance of municipal airports, it can be deduced that the optimal design, if there is one, is not being implemented widely.

The reason for the substandard performance of many municipally-owned airports may be due to the well-documented fact that governments have difficulty managing for-profit businesses in general and airports specifically (Box, 1999; Gilbert, Nicholls & Roslow, 1999; Imundo, 1975). A case-in-point is the new Berlin Airport in Germany: it took nine years to fix the airport's documented 120,000 construction defects. "The supervisory board was full of politicians who had no idea how to supervise the project," Professor Genia Kostka, of the Free University of Berlin, told BBC. "[But] they were in charge of key decisions."[3]

This research posits that airports cannot be reliably measured by profits-and-losses and instead they ought to be measured by their economic impact. A key predictor of economic impact is *operational control*, a new construct of organizational design. The mechanism linking the two constructs is a well-established behavioral construct, *agency theory*. This is impactful research with hands-on implications for the managers of small airports and, more generally, to any organization with geographically or organizationally distant employee-agents.

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[3] Sourced: https://interestingengineering.com/heres-how-berlin-brandenburg-airport-became-one-of-the-biggest-engineering-failures on Nov. 4, 2021.

This research asserts that, *ceteris paribus*, the economic impact of any airport is directly impacted by the organizational design selected by the legal owners of the airport, termed here as *operational control*. Based on the discussion above, the fundamental research question of this study is to measure, to the extent possible, the change in the organization's financial performance attributable to an optimal organization design and, in turn, to measure the agency costs of a suboptimal organizational design.

Research Structure

This paper will proceed in the following manner. First, it will introduce the general parameters of general aviation airports and the economic impact studies which are widely used to measure their usefulness. Stepping back to the bigger picture, in Section 2 the study will explore *agency theory* and in particular the construct of *ineffectual principals*, introduce the construct of *operational control* and examine the methodology underpinning economic impact models. This will lead to insights and generate the hypotheses in Chapter 3. Chapter 4 will deal with the data collection and operationalizations, culminating in the analysis presented in Chapter 5. The regression models will be presented and compared in Chapter 6, along with several validation models. Lastly, and in acknowledgement that this study is just the first examination of a bigger concept, Chapter 7 will frame the conclusions in generalizable terms, suggest specific actions for managers and principals, and consider opportunities for future research.

CHAPTER 2. THEORY AND LITERATURE

Organizational design is a complex trade-off between conflicting pressures; a balance between what is best and what is possible. Speaking specifically to this issue, Hearns, Henshawn & Paisley (2014, p. 98) wrote “Institutional architecture is particularly highly dependent on political, social, economic, and ecological drivers. While form should follow function, these often-competing drivers create a plethora of governance challenges. A one-size-fits-all approach to institutional architecture is neither desirable nor possible in governance.”

This raises two broad questions related to this research: why do organizational structures appear, and why do they persist? Structures offer an organization two benefits. First, a structure creates an environment in which the power of the proposed organization is deployed; like Archimedes and his lever, one needs a place to stand. Structure defines what decisions can be made and who has the power to make them. Second, organizations are stabilizing structures, providing durability and longevity. A “good” structure synchronizes the work of all the individuals inside the organization and minimizes (or at least regulates) the influence of renegades who might take an organization in an undesirable direction. Organizational structure is concerned with power, decisions, and directions. A good, well-fitting structure is important for the performance, efficiency, morale, and effectiveness of organizations (Ambrose & Schminke, 2003; Covin & Slevin, 1988; Lenz, 1980; Dalton, Todor, Spendolini, Fielding & Porter, 1980).

If organizational structures are evolutionary adaptations which enhance survival, it follows that there must be both good and bad adaptations, and the literature has shown this to be true. Prior research has compared (1) centralized to decentralized organizations, (2) good governance to bad, and (3) measures of the span of control, formalization, and specialization (Wynen, Verhoest & Rübecksen, 2014). The general conclusion is that organizational goal-attainment is directly proportional to the quality of the fit (Olson, Slater & Hult, 2005). It is the job of the managers to use the resources of the organization to create rent-producing "resources" — products and/or services which must be scarce, hard to imitate and hard to replace. Good-fitting organizational alignment could be judged as one such critical resource. "Organizational alignments may be the result of chance or skill, but there clearly is a great deal more to superior performance than mere strategic positioning" (Powell, 1992, p. 122).

Given the reasoning above, one would assume that public servants running cities and towns would do everything in their power to identify and implement the "best" organizational design they could discover. Unfortunately, the evidence explored in this study suggests that many do not. At the local level, each community makes different choices about the services the government will offer, and these vary significantly from community to community, depending upon budgets and philosophies. Some towns deal with just the basics: schools, police, streets, and the delivery of sewer and water services. Other municipalities invest in public pools, hiking and biking trails, sophisticated recycling services, downtown festivals and development programs, and even public-private partnerships (Box, 1999). Osborne & Gaebler (1993) suggested that government generally performs a better job at governance, or steering (making policy decisions) than at delivering those services, or rowing. This distinction is at the heart of this research.

Governments and Agency Theory

Most governments have difficulty managing for-profit businesses (Box, 1999; Fountain, 2001; Gilbert, Nicholls & Roslow, 1999; Imundo, 1975). There are vast differences in the ways in which businesses and government operate. The literature suggests that government agencies, while plentiful, are one of the more extreme organizational designs. Unlike a for-profit enterprise, a classical government agency has a highly restricted mission and zone of authority, such as issuing passports or motor vehicle licenses. Agencies are more concerned with fairness in the provision of services, more stable in their operations, serve more intangible social goals, lack competition and so have less incentive to seek cost reductions, and tend to be more procedural and bureaucratic. In contrast, enterprise-style organizations are more dynamic, more focused on learning and satisfying the needs of their markets, have greater scope of action and fewer restrictions, have performance-based budgets and incentives, compete on an equal footing with other private companies, can execute contracts, buy and sell property, operate under their own corporate names, and will close if they cannot compete (Perry & Rainey, 1988; Rosenberg & Ferlie, 2016).

Small municipal airports are an excellent example of the blurry line between the public and private sectors. The confusion of missions, styles, incentives, and management tools impairs the ability of the organization (such as an airport) to maximize its potential (Perry & Rainey, 1988). The cause of this phenomenon can be traced back to one important facet of *agency theory*.

Agency theory is based on a bilateral relationship: that of the owner-principal to that of the agent, employee or subordinate. According to Jensen and Meckling (1976, p. 5), the principal-agent relationship is “a contract under which one or more persons (the principals) engage another person (the agent) to perform some service on their behalf.” In a classical corporate environment, shareholders delegate their authority to a board of directors which, in turn, deputizes a manager to run the organization in the interest of the shareholders.

One of agency theory's basic assumptions is that conflicts can exist between the interests of the principal and those of the agent (Caers *et al.,* 2006). The most commonly studied problems arise when the performance of the agent is distal, cloaked or cannot be precisely monitored (Fama & Jensen, 1983; Davis, Schoorman & Donaldson, 1997). Since any misbehaviors would be undetectable, an unsupervised but rational agent could choose to work in their own self-interest instead of the best interests of the principals, acting opportunistically, shirking duties, or striving for personal profit. This misbehavior deprives the principals of their rightful economic gains and generally are termed "agency costs" (Miller & Le Breton-Miller, 2006; Colombo, Delmastro & Rabbiosi, 2012; Heath, 2009). Agency costs can be minimized with close supervision, carefully crafted compensation schemes, appropriate incentives, financial controls, performance bonds, and/or shareholdings (Donaldson & Davis, 1991; Davis, Schoorman & Donaldson, 1997; Heath, 2009). However, and in sharp contrast with the private sector, these remedies for resolving agency costs generally are not available to public organizations due to their different organizational, financial, and legal systems (Box, 1999; Manimala *et al.,* 2006; Alonso & Lewis, 2001; Imundo, 1975; Dyduch, 2019).

Many government agencies (e.g., the motor vehicle department) are managers of regulatory tasks (e.g., issuing drivers licenses) for which the immediate client may not be the true beneficiary (public safety on the roads) (Box, 1999). This is the heart of the customer service paradox found in many government agencies. This paradox stems from the differences between customers and constituents, as well as the distinction between suppliers and supervisors. True customers need to be persuaded to buy a product or a service while constituents merely need to be aware of the availability of the function. Suppliers are supplicants in front of customers, which have the freedom to say yes or no, while government agencies are supervisors of their constituents, and issuing (or withholding) licenses and permits shape constituent behaviors in ways the constituents may tolerate but may not enjoy. Few free-market companies could survive with a business model based on the forced compliance demanded by the building inspector, the tax appraiser, or the health department. Does the Motor Vehicles Department respond to customers' needs as quickly and sensitively as, say, American Express? Do fire departments have "customers" in the same way that Walmart does? Clearly, most of the functions performed by government are very different than those performed by the commercial sector, and each has evolved practices and procedures optimal for the challenges they face.

But there has been a demand in America and elsewhere to make government more efficient and more business-like. The assertion is that governments should be smaller, more efficient, more competitive, more entrepreneurial, and innovative, and operate with an eye towards "pleasing the customer." The 1990s saw a wave of reform, particularly in Europe and English-speaking Asia, called the "New Public Method" (NPM) of public governance. NPM involved a host of changes including (a) accountability by hands-on professionals, (b) explicit standards and performance measures, (c) an emphasis on results rather than procedures; (d) improved productivity; (e) performance-oriented incentives, and (f) enlightened financial management rather than a fixed annual budget (Brysland & Curry, 2001). The NPM model introduced new economic perspectives such as quasi-markets, private-public partnerships, and commercial (but generic) management tactics (e.g., zero-based budgeting) to governments and agencies (Rosenberg & Ferlie, 2016). It was believed public managers, when freed from bureaucratic regulations, would automatically look for the best ways to steer their organization and would adopt tools that have proven their usefulness in the private sector (Wynen, Verhoest & Rübecksen, 2014). But the traditions, training, values, incentives, and legal restrictions of public service make such transformations difficult. These include the need for accountability, compliance with pre-existing laws, the demand for fair and equal treatment, transparency, social justice and protection of the physical environment (Box, 1999). There can be no doubt the two sectors to this day generally operate very differently.

"Ineffectual Principals" in Government

The discussion above pertains to the differences between for-profit organizations and public agencies, but the focal issue of this study is the fact that small airports are stuck between both worlds. As shown in Table 2, only 37.6% of all airports are available to any pilot, but the vast majority of those airports are the ones owned by governments. Specifically, only 9.3% of all the privately-owned airports in the U.S. are available to the flying public, while 97.4% of the publicly-owned airports are available to any visiting pilot. Almost without exceptions, pilots frequent publicly-owned airports far more commonly than they visit private airports and, in so doing, deliver $1.5 trillion in economic benefit to the country every year (Airports Council Intl., 2018). Airports are important, and even small airports can deliver an unexpectedly significant impact.

The fundamental question studied in this analysis is a condition rarely considered in the literature: are the agents (the airport employees) fulfilling their duties as best they can but are hamstrung in their efforts because the principals are failing in their duties? Undetected or unmeasured agency costs may be caused not by agents failing to deliver for their principals, but because the principals themselves are perpetuating slack performance, undermining

Table 2:

The Ownership and Access of Airports in the U.S.

Types of Airports	Public Use Permitted	No Public Access Allowed	Total
Privately-Owned	825	8,022	8,847
% of Privately-Owned Airports	*9.3%*	*90.7%*	
Public-Owned	4,073	108	4,181
% of Public-Owned Airports	*97.4%*	*2.6%*	
Total, All Airports	4,898	8,130	13,028
% of All Airports	*37.6%*	*62.4%*	

(Notes: This table does not include special-use facilities such as heliports at hospitals. Also, there are an additional 21 military airports open to the public.)

whatever performance their agents attempt to deliver. While the literature of *ineffectual principals* is normally focused on corporate boards and their governance (Arnwine, 2002; Erturk, Froud, Johal & Williams, 2004), prior research hints at exactly the lackluster outcomes found at many airports (Caers *et al.,* 2006). There are contextual elements to this discussion as well; Firth, Fung and Rui (2006) studied the rate of change among board members in a third-world economy with less rigorous rules-of-law, and Jiraporn, Singh and Lee (2009) considered the effectiveness of boards where their members "polished their resumés" by serving on a multitude of boards and committees. This contrasts quite pointedly with the more commonplace scenario proposed by Davis, Schoorman and Donaldson (1997), where losses to the principal are the result of action (or inaction) by a wayward agent. These researchers recite the long list of responses noted above that principals can use to impose controls upon the agent to reduce agency costs (see also: Tahir, Nazir, Qamar & Boyer, 2022).

Rarely is there a discussion of the actions an agent can take when the principals are failing at their jobs.

It is useful to recall that most private-sector boards attempt to include among their members persons with relevant skills and/or experience. This is not true in public service. The principal skill exhibited by an individual in government is the ability to get elected. Consider the talents, training and motivations of the principals attempting to run a government-owned businesses, in this case, a small airport. The ultimate governing bodies (the legal owners) are town or city councils populated with politicians who respond to public pressure rather than strategic organizational needs or economic incentives (Baum & Wally, 2003; Meyer & Brown, 1977; Pastoriza, 2008). The principals will be ill-informed about the voluminous legal, regulatory, financial, and technical nuances of airport operations (Caers *et al.,* 2006). Unlike commercial firms, information flows up and down the organization hierarchy will be hindered (Baiman, Larcker & Rajan, 1995) and vital airport performance benchmarking will be rare (Linsenmayer, 2013). Employee incentives will be minimal and job engagement will be low, suppressing creative customer-focused decision-making or spontaneous organizational citizenship behaviors (Macey & Schneider, 2008). Those employees directly tasked with running the airport will not be incentivized to find new markets or technologies. Industry "best practices" will neither be examined nor disseminated, employees will not go to industry seminars or trade association meetings, and goals will be poorly configured by ill-informed politicians so weak performance may continue for years (Faran, 2017; Raisch & Birkinshaw, 2008). Their ineffectiveness and unawareness will generate an emphasis on maintaining the "good enough" status quo as opposed to dynamic innovation (Teece, 2007; Faran, 2017).

Human beings are "social creatures" embedded in a web of relationships with others that are part and parcel to the accomplishment of on-the-job tasks. These relationships exist for both the "formal relations of authority" (a "mechanistic" mode of operation) and the less structured links "across departmental and hierarchical boundaries" that hold organizations together (sometimes termed "organic" organizations). When the formal organizational structure diminishes or defeats organic networking opportunities, organizations will fail (Ambrose & Schminke, 2003; Burgelman, & Grove, 2007; Hunter, 2015). It has been the repeated observation of this condition by the author which has fostered the hypotheses at the core of this research, specifically that the worst airports will be run as government agencies (a condition of low *operational control*) while the best-run airports will be those operated as customer-oriented enterprises, independently and at an arm's length from the local government (a condition of high *operational control*).

Accounting Procedures as a "Straw Man"

The assertion that governments are ill-suited to running for-profit businesses is an essential element in this research and, as a fundamental assertion, deserves a degree of scrutiny. A good technique to better understand this issue is to pick a function performed by both governments and businesses and compare them operationally. One representative and well-explored example might be the accounting systems used by the two types of organizations, and while this explication is lengthy it is probative.

Generally, a firm's management accounting system serves two functions. First, it is the principal management tool by which a firm's operational condition is judged on a day-to-day basis. Secondly, it is the long-term scorecard by which success is defined at the end of the year. The rules and procedures of managerial accounting play a key role in the design, administration, and operation of organizations (Gupta & Bhatia, 2005).

It is appropriate to consider the effects of an inappropriate accounting system. Such a system is defined as one that is ill-fitted to the current needs of the business (Hartman, 2005). The effects of poor "fit" ripple through a firm. Managers may not receive timely financials or may not have confidence in the relevance or accuracy of those reports. Key performance indicators (KPIs) will not be collected, computed, or disseminated. Pricing and purchasing decisions could be based on erroneous data. The firm's ability to set reasonable strategic goals, track benchmarks, measure progress and make data-driven decisions could be degraded (Malíková & Brabec, 2012). In the worst case, poor-fitting accounting systems could lead to major financial losses and possibly even bankruptcy (Abu-Musa, 2005).

Municipal accounting systems almost invariably use "fund accounting" which is a form of accounting focused on accountability and less on tracking profitability. The focus of fund accounting is to monitor revenue inflows — including taxes, fees, fines, and grants — and link those to the process on which those funds are spent (Fluckiger, 1963). Unlike for-profit business, monies cannot easily be moved from one fund to another (Gorr, Lynn & Freeman, 1976). In fact, in municipal accounting systems, a budget is defined by law and is passed annually by the municipality (usually termed "the budget ordinance"). Variations from expected spending require changes to the ordinance, with public meetings and votes by the appropriate public officials.

Financial statements and the management procedures prepared for government agencies can be quite different than those prepared for-profit stakeholders (Herzlinger & Sherman, 1980; Baiman, Larcker & Rajan, 1995). In North Carolina, all municipalities are required to use the MUNIS financial system to simplify auditing and accountability processes. MUNIS is a full-featured enterprise resource planning ("ERP") system produced by Tyler Technologies of Plano, Texas. The integrated system is designed for not-for-profit government agencies and can manage revenues, expenses, financial reports, procurement, human resources, payroll, and audits. It does not compute gross profit, does not offer tools for margin analysis and cost-of-goods sold, and is poorly structured for frequent price changes (aviation fuel prices change daily at the busiest airports). Municipal accounting systems do not have "customer-friendly" features such as app interfaces and loyalty cards, nor do they offer discounts to high-volume customers (Mattingly, 2001; Jones, 2002). A system that smoothly generates annual property tax bills can be very clumsy if it needs to quickly generate jet fuel invoices or accept credit card payments.

There are other problems attempting to use municipal fund accounting software in a competitive, for-profit environment. Fund accounting systems record the expense of long-term capital improvements as they occur (Herlinger & Sherman, 1980) rather than amortizing them over their expected lifespan. This process produces extreme swings in profit and loss. Consider a mid-sized airport which generates $5 million in annual revenues and produces $100,000 in profits each year. Further assume that at some point management decides the runway has reached the end of its useful life and needs to be repaved, for a cost of $10 million. 90% of those repairs will be funded by federal grants, but the airport will need to contribute $1 million from its own resources. In fund accounting, this produces two extraordinary outcomes. First, the $9 million federal grant will be shown as revenue, misleadingly causing the airport to appear to have ballooned to a $14 million business. Secondly, the $10 million paid for the repaving will be treated as an expense in the year it occurred, causing the airport to record a deficit (loss) of $900,000. Both conclusions would be incorrect in a commercial setting but are correct under fund accounting. This means the common financial benchmarks used in the commercial sector — profits, losses, return on assets, etc. — will be misleading when applied to for-profit businesses run by governments and will be unstable when applied to year-over-year comparisons.

While no one would disagree that accounting systems should be stable and reliable, excessively rigid systems may undermine the functionality of the enterprise (Baiman, Larcker & Rajan, 1995). It is hard to imagine any successful for-profit commercial enterprise operating for years without revamping their information systems but that's exactly the modus operandi of many municipalities. It is likely that the airport's financial management system reflects a sub-optimal, obsolete, and even ill-informed municipal decision made years ago.

For example, financial reporting is just one function at a small airport. Also needed are purchasing systems, payroll processes, incentive programs, human resources procedures, and legal services. While the configuration of these systems may be ideal for government agencies, they probably will be ill-fitting and constraining to the efficient operation of a competitive business. This author has found that airports operating under fund accounting systems often develop and procure alternative software "workarounds" simply to function on a day-to-day basis. These systems subsequently require additional back-office chores (spreadsheets or manual entries) to feed the daily transactions into the fund accounting system. The cost of these work-arounds —in terms of man-hours, cognitive effort, and managerial energy — may produce a cumulative burden of inefficiencies so great that the airports are unable to perform at their highest level because they are distracted by uninformative reports, awkward workarounds, inappropriate employee incentives, the inability to hire the best people, and other weaknesses.

There are other implications stemming from requirement to run a for-profit business using a not-for-profit accounting system. Information flows up and down the organization hierarchy will be clumsy, uninformative, or stunted (Colombo, Delmastro & Rabbiosi, 2012) because the financial system will not record or report vital key performance indicators. Comparative sales or performance benchmarking will be rare (Linsenmayer, 2013). If the airport is required to offer traditional municipal benefits to employees and manage them using traditional payroll systems, employee incentives and job engagement may be low, suppressing creative customer-focused decision-making or spontaneous organizational citizenship behaviors (Macey & Schneider, 2008; Manimala, Jose & Thomas, 2006). The ultimate legal owners — the politicians — may be busy with other duties (e.g., schools, sewers, and roads) and generally will be ill-informed about the financial, legal, regulatory or technical nuances of airport operations. Their unawareness will generate an emphasis on a status quo as opposed to the essential dynamic innovation (Teece, 2007; Burgelman & Grove, 2007).

However, some airports are permitted by their political owners to operate with a higher degree of *operational control*. These airports generally use commercial-style management systems (“Total FBO” and “Atlas” are two leading commercial examples). These can track the correct key performance indicators, deploy financial information systems which closely resemble for-profit systems, and will have more flexible human resource, payroll and incentive systems. In these cases, customer service will be rewarded and intrapreneurship will be valued. The best-run airports may be those operated at arm’s length from the local government.

"Operational Control" as the Independent Variable

The literature tells us that it should be possible to predict the performance of a firm by characterizing the fit between that organizational architecture and the strategy being implemented (Pugh, Hickson, Hinings, McDonald, Turner & Lupton, 1963; Faran, 2017). This study attempts exactly that task: to quantify the link between the performance of a firm to the fit of its organizational structure. The fundamental assumption in this study, based on the author's decades of experience in the industry, is that most small airports generally face similar operational, financial, regulatory, and marketing problems. Over the years airports should have evolved organizational structures optimized to maximize their performance. In all likelihood that optimal design would be very similar across most airports. It is expected that the degree of such fit with the optimal configuration would explain a significant portion of the variance in the organization's performance, over and above any variance caused by economic, geographic, or demographic variables. A corollary of this assertion should be that airports which vary from the optimal configuration would be expected to suffer performance deficiencies proportional to the degree of that variance. In short, organizational fit acts as a source of competitive and operational advantage. This advantage enhances the collection, analysis, and dissemination of knowledge throughout the organization which in turn enables an enhanced ability to understand, internalize and act upon that information even in uncertain environments (Powell, 1992; Tushman & Nadler, 1978; Hunter, 2015).

A new construct, *operational control*, is postulated in this study to be an organizational design choice made by the legal owners of a facility which defines the people, practices, resources, and policies deployed to operate that facility. This research posits that *operational control* is the degree of delegation authorized by the legal owners to the day-to-day managers of a firm (Rivkin & Siggelkow, 2003). *Operational control* directly effects down-stream resources such as budgets, personnel, training, and the professionalism of the airport management team, and through them, the financial performance of the firm — by directly or indirectly "shaping the resource allocation decisions and distinctive core competencies of the firm" (Miller & Le Breton-Miller, 2006, p. 75).

This paper posits the degree of *operational control* should be "low" when an airport is operated inside a local government, as when the airport is managed as part of the highway department. For example, Hendry County, Florida has chosen to have the local airport operated by the county engineer's office, which also manages the county roads, bridges, and cemeteries. The highest levels of *operational control* should occur when the airport operates as a sovereign political entity, roughly equivalent to a town, or is completely privatized. An intermediate condition would be managing an airport inside a local government but with some degree of separation or specialization, such as the airport having a distinct budget. For the purposes of this study, *operational control* is operationalized as a categorical (dummy) variable denoting this condition, but future research may find ways to characterize this condition using ratio-scale measurements.

Operational control is highly generalizable. While the focal organizations for this study will be general aviation airports the construct is expandable to other organizations, commercial firms and not-for-profit organizations, especially organizations (a) physically or economically distant from their legal owners, (b) using technologies and processes distinct from their legal owners, or (c) those instances where there are legally-defined separations up and down the organizational chart, such as the relationships between franchisees and the parent franchisor.

It may be useful to consider *operational control* in terms of the organizational structure in which the airport is embedded. As a matter of background, some airports are identified in the FAA data as being operated by airport authorities, commissions, agencies, or bureaus which have relatively limited interactions with the rest of the municipal government. This can be termed a “single-function” organizational design; the sole function of the authority is to operate the airport. Other airports are identified in the FAA data as being integrated into the day-to-day function of the government which can best be defined as a “multi-function” organizational design. In a multi-function configuration, the task of managing the airport is just one chore amongst the many assignments given to that agency, such as running the city parks or the highway department.

Operational control is conceptualized to be “low” when an airport is operated inside a multi-function organization, and the needs of the airport are just one of many claims upon that department’s managerial time, budget, and equipment. In the experience of the author, subordinate entities within a multi-function organization generally will not have separate staffs, distinct budgets, industry-specific technical expertise, or dedicated support systems such as payroll, benefits, or human resource systems. They will have little or no incentive to improve the operations of the firm nor to respond to customers.[4] In contrast, the highest levels of *operational control* occur when the airport operates as a sovereign political entity in a single-function organization dedicated to running the airport. In this case, the airport would have a management team completely focused on the needs of the airport and its customers.

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[4] As a case in point, in January 2023 the author attended a hangar party at a distant airport. That field is a satellite airport outside a large metropolis. Among the 235 airports in this study, this particular airport is rated #32 in terms of population and #20 in economic intensity, so it would be expected to be an economic dynamo. However, it scored #110 in terms of economic impact. During that event, the lethargy of that airport was discussed among the pilots in the group. “Our airport manager thinks he has only one customer,” one pilot said, “and that customer is the city manager.”

They would have every incentive to be responsive to pilots and passengers, to develop new capabilities, to enhance their technologies, forms, and practices (Levinthal & March, 1993), to operate in an economically sustainable manner, and manage the budget and investment decisions in the best interest of the airport itself undistracted by the demands of other departments and budgets. In most situations, such organizations are created by the state legislatures and have roughly the same legal authority as a town or municipality, including the authority to impose taxes and/or eminent domain. An intermediate hybrid condition would be managing an airport inside a local government with some degree of separation, such as one with a distinct budget or being managed as a satellite airport supporting a larger, more prominent airport.

It may be useful to note that *operational control* often is an artifact of the airport's history and usually is not a deliberate managerial decision by today's legal owners. In anecdotal discussions with a non-random sample of more than a dozen airport managers, only one was familiar with the specific decision to establish the organizational structure for the airport. The remainder reported it had simply "always been that way." It is hard to imagine any successful for-profit commercial enterprise operating for years without revamping their organizational chart. It is possible that the current degree of *operational control* reflects an unchallenged and unconsidered decision from years and potentially decades ago, potentially sub-optimal and obsolete.

Related Constructs

Operational control is distinct from several organizational design constructs which have some similarity or overlapping attributes. For clarity, the following discussion identifies these constructs and considers the differences and similarities outlined in the literature, while Table 3 briefly summarizes the comparisons.

Operational control is distinct from *legal ownership*. In most instances, the legal owner of an airport is a local municipal government. Verhoest (2002) found the control perceived by executives and managers could (and did) diverge substantially from the formal legal structure of public agencies as defined in legislation and regulations. It is expected that *operational control* offers a glimpse of the freedom managers think they have and hence a method of measuring the actual functioning of agencies (Wynen, Verhoest & Rübecksen, 2014). *Operational control* also describes the processes used by the manager to allocate resources and set priorities and is irrespective of the holder of the title to the land or buildings. As conceptualized here, *operational control* has a contextual element and may be expanded or diminished by the success of the managerial team. Poor performance by the managers (such as deferred maintenance, deficits, low productivity, or lack of innovation) can attract complaints which generate public criticism and may result in intervention by the legal owners. A tradition of strong, positive performance can be a source of delegated power as the legal owners divert their attention to more problematic departments (Lioukas, Bourantas & Papadakis, 1993).

Operational control also is distinct from the regulatory constraints and operational guidelines imposed upon an airport by the FAA. For example, most municipal airports will have a robotic weather station. This investment is required by the FAA if the airport desires to have an instrument approach which allows airplanes to land and depart in poor weather. The presence or absence of these devices is a federal decision and is only indirectly affected by the degree of *operational control*.

Operational control is related to but distinct from the continuum of *centralization/ decentralization*. There is a large body of research on the "height" of organizational structures ("flat" vs. "tall"). Centralized decision-making involves determining where the locus of decision-making authority lies within an organization (Pugh et al., 1968; Brock; 2003) and measures the extent decision-making is concentrated in a single point or diffused throughout the organization. Other researchers have shown that a centralized organization assumes two conditions: (a) the presence of fully informed and relatively more expert decision-makers at the higher levels of the hierarchy, and (b) sufficient information processing capabilities to make decisions in a timely and accurate manner, lest an information bottle-neck form at the top of the organization (Rivkin & Siggelkow, 2003). Research also has shown decentralized organizations have three consistent attributes. First, fewer tasks are delegated to business unit managers when the principals up the hierarchy have more expertise, which is not the case in this scenario (Baiman, Larcker & Rajan, 1995). Second, the models predict fewer decisions will be delegated to subordinates as a business unit's relative importance increases; in other words, "the more important the subordinate firm, the more decision-making is performed centrally" (Khandwalla, 1973). This usually is not the case with municipal airports because they are viewed by politicians as less critical than schools, roads and public utilities. Finally, decentralized management structures tend to be found in more dynamic industrial segments such as software or advertising. Since the politicians acting as the legal owners of the airport satisfy none of these criteria, *centralization/decentralization* is a related but distinct construct with respect to *operational control*.

Table 3:

A Comparison of Organizational Constructs Similar to *"Operational Control"*

Construct	Definition	Differences	Research & References
Legal Ownership	A term of law defining the person(s) who hold title to a specific asset or property, empowering (a) the right to possession, (b) the privilege of use,and (c) an enforceable claim recognized by law. (Ref: https://www.britannica.com/ topic/property-law#ref28469, downloaded Oct. 2, 2022)	Owners of property have the right to buy, sell or transform their properties while agents such as airport managers and employees generally do not have that unrestricted authority. *Operational control* is a subset of property rights which owners may choose to delegate to agents.	Verhoest (2002) found managers could diverge substantially from the formal legal structure of public agencies as defined in legislation and regulations.
Regulatory Requirements	Regulatory agencies resist delegating authority to their targeted organizations but can force compliance upon their targeted organizations, imposing costs, minimum standards, and constraints on operations (e.g., FAA Grant Assurances)	The presence or absence of regulatory compliance represents the imposition of an exogenous decision by one agency upon another and, as such, is not a new capability or feature desired by or developed internally by the agency/airport. These constraints are independent of the degree of *operational control*.	The degree of compliance with regulations is enforced by penalties imposed upon firms or managers. A history of strong, positive performance can be a source of derived or delegated power as those regulators divert their attention to more problematic departments (Lioukas, Bourantas & Papadakis, 1993).
Centralization/ Decentralization	A continuum predicated upon the location of decision-making authority within an organization; a single point or diffused? (Pugh et al., 1968)	Decisions made "higher" in the hierarchy are improved because of (a) better-informed and more expert decision-makers at the higher levels of the hierarchy (b) operating with sufficient information processing capacity to digest information accurately. In this research, it is posited that the politicians supervising an airport satisfy none of the prerequisites for centralized decision making.	The "height" of organizational structures (Rivkin & Siggelkow, 2003); the locus of decision-making authority (Brock, 2003); the effect of size upon centralization (Donaldson, 2001), constraints on organizational tasks and organizational age (Wynen, Verhoest & Rübecksen, 2014), the relative importance of the firm to the overall organization (Baiman, Larcker & Rajan, 1995; Khandwalla, 1973).
Organizational Autonomy	Defined as the extent to which an organization can allocate resources and make independent choices outside of a legal or organizational hierarchy (Pennings, 1976)	A relative condition capturing the degree of interdependence of the focal organization with sister organizations in the same overall entity (a purchasing department, human resources, legal, etc.). Small airports have little functional interdependence with other governmental departments because they are controlled by different aeronautical regulations and different sources of funding.	Organizational autonomy defines the scope of decisions senior managers relative to the interdependence of similar tasks within the larger organization (Oliver, 1991; Verhoest et al., 2004; Wynen et al., 2014). Some researchers postulate organizational autonomy is an antipode to centralization (Pennings, 1976). Some research on public sector organizations found a correlation between a lack of organizational autonomy and more centralized decision-making (Brock, 2003).
Personal Autonomy	Defined as the degree a job provides substantial discretion in (a) scheduling work and (b) in determining operational procedures (Hackman & Oldham, 1975)	A highly individualized, context-specific assessment by a person of their job. Sub-facets include experienced responsibility, experienced meaningfulness, skill variety, task identity, task significance, method autonomy, scheduling autonomy and task choice autonomy. Differs from *operational control* in being highly ideosyncratic as opposed to an organizational condition.	Operational control is an organizational construct, not a personal or individualized one. None of the sub-facets of personal autonomy are conceptualized as elements of operational control, particularly as they pertain to highly technical organizations such as airports (Ryan & Desci, 2000; Bakker & Demerouti, 2008; Greenhaus & Callanan, 1994; Breaugh, 1999; Kiggundu, 1983).
Managerial Discretion	A personal, ad-hoc, executive-based behavior of deploying resources to achieve organizational goals without reference or inhibition from other organizations (Hambrick & Finkelstein, 1987).	Frequently found in dynamic environments, decentralized organizations, and/or situations with transformational leadership. Controlled by both external factors (differentiated products, market growth, industry structure, demand stability, quasi-legal constraints, and capital intensity (Hambrick & Abrahamson, 1995) and by internal factors (job demands, rules, routines, explicit contractual obligations). Differs from operational control in that it is an individual behavior that is leadership-based.	Three key traits of *managerial discretion* are (a) the willingness of a leader to deploy resources (b) in an ad-hoc manner, outside of the traditional or expected mechanisms (c) without direct guidance from other organizations (Wangrow, Schepker & Barker, 2014; Arambula, 2008; Hambrick & Finkelstein, 1987; Migue & Blanger, 1974). Such behavior would be inimical to the safe and efficient operation of an airport.

Operational control also is distinct from *personal autonomy. Personal autonomy* has been operationalized somewhat casually by a variety of researchers, to the extent of providing conflicting measurement scales and diverse conclusions.[5] That said, the construct generally pertains to “the degree to which the job provides substantial freedom, independence, and discretion to the individual in scheduling the work and in determining the procedures to be used in carrying it out” (Hackman & Oldham, 1975, p. 162). It is a highly personal assessment by a person of their specific job at one point in time and should not be generalized or attributed to the organization at large (Ryan & Deci, 2000). As an example of the manner in which context can warp personal autonomy, Breaugh (1999) found that part-time workers in an organization generally have less education, less training and less job-related experience than full-time workers and hence less autonomy. He attributed this condition to the supervisors who felt that part-time workers were not worth the investment in training that precedes providing job autonomy. Another point of differentiation is the diverse set of sub-facets for *personal autonomy* which have been developed by researchers, including experienced responsibility, experienced meaningfulness, skill variety, task identity, task significance, method autonomy, scheduling autonomy, and task choice autonomy (Greenhaus & Callanan, 1994; Breaugh, 1999). None of these terms are conceptualized as sub-constructs of *operational control*, particularly as it pertains to highly technical organizations such as airports. One can only imagine the chaos which might be caused if each employee decided

[5] Vague definitions lead to inconsistent conclusions. In one of Breaugh's early studies of autonomy (1985) he developed an example of conflicting autonomy measurement scales using the example of a bus driver. As he noted, a bus driver has little control over the schedule, route, or pace of the job. Most autonomy scales would rate the driver with low autonomy, as a driver has little control over the task. But Hackman & Oldham's (1975) autonomy scale looks to other criteria — the driver spends most of the day alone, is generally unsupervised, and usually lacks interaction with other workers — which would rate the task as highly autonomous.

their own "best way" to refuel an airplane (Ryan & Deci, 2000; Bakker & Demerouti, 2008; Kiggundu, 1983).

Operational control also is distinct from *organizational autonomy*. *Organizational autonomy* is defined as the extent to which an organization can allocate resources and make choices on strategic questions independently of its legal or supervisory hierarchy (Pennings, 1976). *Organizational autonomy* defines the bounds or scope of the decisions senior managers may make as a function of the interdependence of any specific organizational tasks (Pennings, 1976; Oliver, 1991; Verhoest et al., 2004; Wynen, et al., 2014). Some researchers postulate *organizational autonomy* is the orthogonal antipode to the construct *centralization/ decentralization* (Pennings, 1976) described above. But *organizational autonomy* is a relative condition which requires a baseline case against which autonomy may be compared. For example, a town may have a purchasing department for most of its needs, but the town's school system may have its own autonomous purchasing function because of the volume of transactions or the specialized knowledge needed to manage the acquisition process. In this case, the school system might be deemed to have greater *organizational autonomy* than the town's other departments — but only in regards to purchasing. It is plausible an airport might have greater *organizational autonomy* than another government agency, at least for a restricted sub-set of tasks but this is different from *organizational control*.

There also is a body of research into public sector organizations into *functional interdependence*. This construct is defined as the degree to which two or more organizations rely on each other, generally operating separately but husbanding scarce resources by relying on each other as a trusted resource of services or expertise in narrowly-defined areas. As a hypothetical example, a school system and an airport might save money by jointly sharing human resources functions but otherwise operating separately from both each other and the rest of the government functions. In instances of *functional interdependence* study by other researchers, not-for-profit managers tended to rely on more centralized decision-making than commercial enterprises (Brock, 2003). This differs from *operational control* in that airports have little or no functional dependence upon the other departments in public government — despite superficial similarities, runways are not roads, terminals are not school buildings, and purchasing jet fuel is different than buying schoolbooks. Any perceived interdependencies between an airport and other governmental departments usually would be a case of fitting a square peg into a round hole; even the tarmac used to pave runways has a different composition and specification than the asphalt used to pave roads. The sole exception might be in the case of financial reporting, where centralization might offer modest benefits from a security and audit perspective, but as we will see below even that interdependence works against the success of the airport.

Lastly, *operational control* is distinct from *managerial discretion. Managerial discretion* is defined as an ad-hoc executive-based behavior manifested as the latitude to deploy resources to ensure the achievement of organizational goals without direct reference to or inhibition from other organizations or formal rules (Wangrow, Schepker & Barker, 2014; Arambula, 2008; Hambrick & Finkelstein, 1987; Migue & Blanger, 1974). While *managerial discretion* is more common in specific job-tasks, certain environments, and under certain organizational structures, it is principally controlled by the personal characteristics and leadership styles of the executive involved. Research has identified six specific intra-firm conditions which mediate the relationship between managerial discretion and firm performance (task autonomy, management incentives, management compensation, employment contracts, job demands, and structured routines). Meanwhile, a long list of factors external to the firm — differentiated products, market growth, industry structure, the stability of demand, quasi-legal constraints, the presence of powerful outside forces, and capital intensity — have been found to suppress *managerial discretion* (Hambrick & Abrahamson, 1995; Yan, Chong & Mak, 2010; Espedal, 2015). Some scholars have adopted a hostile view of *managerial discretion* as vulnerable to self-serving actions, due to limited accountability and higher agency costs (Fama & Jensen, 1983; Arambula, 2008; Migue & B1anger, 1974). In either case, *managerial discretion* clearly is an individual construct linked to the behavior of a leader, not an organizational activity. *Managerial discretion* also is linked to the decentralized side of the *centralization/ decentralization* continuum and would be inimical to strong organizational constraints. High levels of *managerial discretion* would be a poor fit with a well-run airport.

"Economic Impact" as the Dependent Variable

The current study argues the optimal measure of an airport's effectiveness is the economic impact it delivers to its community. Economic impact is an economic measure developed using input-output models, and since this construct is at the heart of this research it is reasonable to briefly explain the derivation of this data. As noted above, traditional financial measures such as profit or return on investment are unreliable in the airport industry. Furthermore, most organizational design studies neglect to use financial data as a measure of firm performance. In fact, a review by Dalton and colleagues (1980) found financial performance to be deployed as the dependent variable in only two cases.

Input-output models were first developed by Russian economist Wassily Leontief in the 1930s in an early attempt to understand and quantify the complex relationships found in inter-dependent economic systems. Leontief's crucial contribution was to recognize an economy was composed of distinct sectors, and each sector both accepts inputs from the other sectors and sends outputs back into them as well. No sector is an island; each sector depends on others. In 1973, Leontief won the Nobel Prize for this work.

While input-output models are complex, their conceptual simplicity, the ability to elucidate the complexity of large-scale systems, and the well-known concept of "multiplier effects" (described below) make it a widely-accepted tool by both practitioners and academics (Canada, 2017). It is a powerful methodology for assessing not only the direct impacts of an observed economic process but the exogenous impacts of disruptive events, as long as the focal economic systems have measurable interdependencies (Yu, 2018). Because of this power, flexibility and conceptual simplicity, I-O models have been used for more than fifty years to study the ebb and flow of an enormous variety of activities, including the effect of a new convention center on tourism spending in Orlando, FL (Braun, 1992), the economic impact of the 9/11 terror attacks (Santos, 2006), the adequacy and efficiency of public schools in Pennsylvania (Kuhns, 1973), the regional social, economic, and environmental effects of a flood control system in Arkansas (Liew & Liew, 1980), changes in greenhouse gas emissions resulting from international trade (Wiedmann, 2009), the impact of imposing tolls on heavy trucks on the German autobahn (Yu, 2018), the environmental impacts of coal-fired electricity development in Australia (James, 1983, cited by Lenzen, Murray, Korte & Dey, 2003), the effects of a major earthquake (Kim, Ham & Boyce, 2002), and tourism expenditures (Frechtling & Horvath, 1999).

I-O modeling has many attractive features. Unlike many statistical techniques, a precise theoretical model is not necessary because I-O modeling is a data-driven exercise.

Missing values are less critical in I-O models; in many models, only a few cells in the matrix have meaningful entries and it is often assumed the smaller values either can be ignored because they are trivial or because the precise values are difficult to establish (Hendrickson, Horvath, Joshi & Lave, 1998). Lastly, data can be expressed in any metric (tons, miles, kilowatts), but monetary values are often preferred as they are easily expressed, consistent, easily converted and highly understandable.

There are important nuances to I-O modeling which limit (or at least shape) the applicability of the technique. First, input–output analysis is a top-down approach to describe the behaviors of large, complex, and inter-related entities. Since it is a simplification, it can overlook important subtleties and non-linear relationships (Yu, 2018; Lenzen, Murray, Korte & Dey, 2003). Second, the technique models interactions between entities purportedly with definitive boundaries. Defining those boundaries can be challenging and expensive because of the extensive data requirements, especially at local levels or internationally. It has been noticed that errors in boundary definitions can produce deceptive results. Hendrickson and colleagues (1998, p. 187) wrote, "The selection of boundaries [is] typically a simplification of the problem, reflects conventional practices, and assumes neglected inputs are unimportant... [However] small inputs may leverage major portions of the calculated aggregated outcomes." (See also: Lenzen, Murray, Korte & Dey, 2003; Kuhns, 1973; Frechtling & Horvath, 1999). Third, I-O models normally assume all inputs and outputs within a sector are linear and homogeneous (e.g., an X% increase in the output of product is assumed to always increase costs by Y%). This means I-O models have difficulty deciphering the confounding effects of non-economic and/or non-linear factors such as quality, innovation, or efficiency (e.g., Walmart and Nordstroms are both retailers but offer very different experiences) (Santos, 2006; Yu, 2018). The precision or granularity of a model can ameliorate this condition to some degree (moving from two-digit SIC codes to four-digit codes, for example) but at the cost of exponentially increased data collection requirements (Hendrickson et al., 1998) and local data may need to be imputed from state or national databases. Questionnaires and surveys may be needed to fill in the gaps (Stevens, Treyz, Ehrlich & Bower, 1983). Finally, marginal analyses are challenging to implement in I-O models as consideration must be given to the relative scarcity of inputs and their incremental contribution to the outputs, as some inputs are more expensive than others and pricing may not be linear (Yu, 2018; Kuhns, 1973).

In the United States, the Bureau of Economic Analysis (BEA) aggregates input-output data on the U.S. economy. The summaries are updated annually and provide information on 71 industrial categories. More detailed input-output benchmarks are produced every five years for 405 industrial groupings. BEA's industry groupings generally follow the North American Industry Classification System (NAICS) descriptors. Generally, the BEA data are the "controlling sources" used by commercial input-output systems when companies develop their proprietary input-output models[6].

The FAA has found the commercially-available IMPLAN input-output economic model to be useful in assessing the effects of airport investments. Developed in 1976 under the direction of the United States Forest Service, IMPLAN was one of the earliest computerized economic impact modeling systems and required mainframe computers. In 1986 the system was transferred to the University of Minnesota which was tasked to expand and update the original offering. The organization was privatized in 1993 under the name Minnesota IMPLAN Group, Inc. Today the company operates as IMPLAN Inc., is based in

[6] Source: https://implan.com/data, downloaded on Sept. 9, 2022.

North Carolina, and the IMPLAN application now runs on desktop computers. The principal function of the company is updating and improving the resolution of the regional, national and international input-output data sets. IMPLAN uses the BEA data and supplements it with data from the Department of Agriculture, the Bureau of Labor Statistics, the Department of Commerce, the U.S. Census, and international data for 37 industries in 64 countries[7]. As noted previously, at least 36 states and three countries have concluded that economic impact is a valid measure of an airport's contribution to their economies, and 26 of those used the IMPLAN model for their economic impact studies of their airports.

There generally are three major components of economic impact: direct impacts, indirect impacts, and induced impacts. All three are relevant to airports (Yu, 2018; Santos, 2003; Frechtling & Horvath, 1999; Canada, 2021; United Kingdom, 2015; see also the state-by-state economic impact studies listed in Attachment 1). *Direct impacts* are the actual spending by the target sector, and include the wages, benefits, spending and other economic outputs that can be attributed to each individual airport. Importantly, this includes activities not just of the airport itself, but also all the relevant spending by the companies and individuals based at the airport or frequently use the airport facilities, such as flight schools and airport restaurants (Hendrickson, Horvath, Joshi & Lave, 1998).

In contrast, *indirect economic impacts* are those that develop as a result of the direct impacts, specifically looking down-stream at people, companies and/or industries that benefit from the focal activity. For example, airplane fuel is delivered by truck to small airports. Some small proportion of the total economic activity of those trucking companies goes to support that airport's activity and accumulates as an indirect impact associated with that

[7] Source: Ibid, downloaded on Sept. 9, 2022

airport. Similarly, the accounting, insurance, security, maintenance, and legal services used by aircraft owners, operators and airports are classified as indirect impacts as well. The decision-calculus is simple: if the airport was closed, the stimulus provided by both those direct and indirect impacts would be lost to the community.

Induced impacts are the third type of economic energy added into the ecosystem. Induced impacts are the multiplying "ripple effect" of spending on services, supplies, wages and profits earned in the course of both the direct and indirect economic activities. This is often described as the "household" spending impact (Lenzen, Murray, Korte & Dey, 2003). The Indiana (2012, page 6) airport study offers a pertinent example: "If a flight instructor takes his or her paycheck and buys lunch at a local restaurant, that money supports the payroll for the waiter, cook, and busboy at the local restaurant. [They…] in turn spend their paychecks on childcare, groceries, or other items, continuing the cycle until those dollars may eventually leave the community." Direct and indirect spending splash into the local economy, creating ripple after ripple, until the ability to discern the ripples is eventually lost in the background noise.

Induced impacts can be of infinite order and can be (and frequently are) geographically and temporally distant from the initial economic activity, perhaps even rippling into foreign countries. As Lenzen and colleagues (2003, p. 264) wrote in a highly relevant example discussing environmental impacts, "In the case of building an airstrip, for example, [these effects] not only include environmental pressure exerted by the airstrip itself (impacts on vegetation, wildlife and the physical environment), but also the land occupied by producers of construction machinery, by the steel plants producing the steel for the machinery, by mining operations providing the coal and iron ore for the steel factory, by the manufacturers of mining equipment, and so on." Great care must be taken when building the boundaries of regional or national I-O studies, as Lenzen and colleagues noted, because the errors introduced by multiplying induced impacts can be far-reaching.

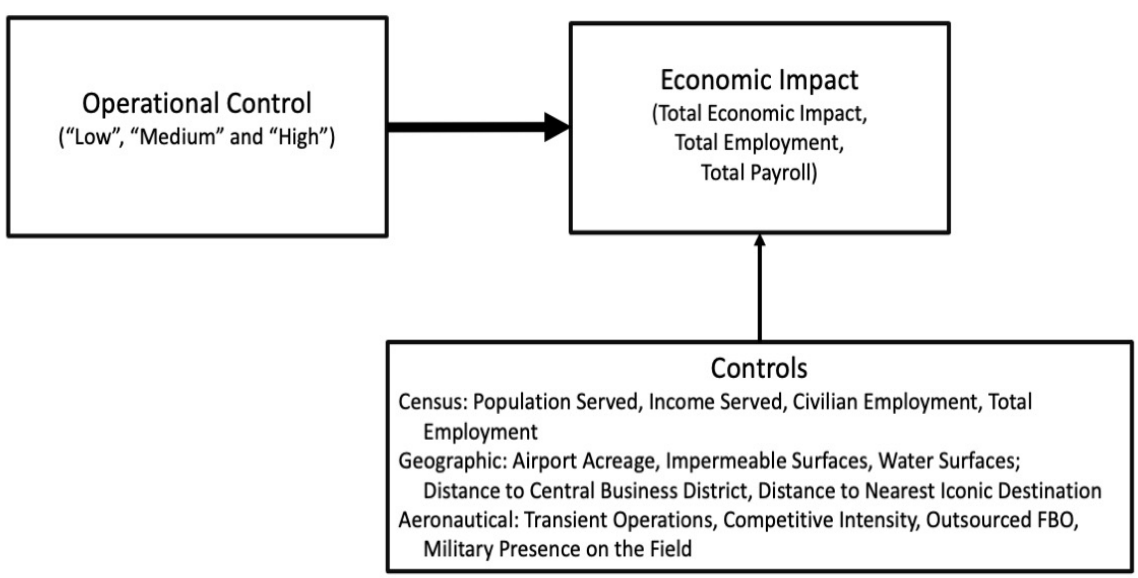
A simple I-O model can be conceptualized as a spreadsheet: inputs on the left, outputs along the top, and sums either along the bottom and the side summing the total inputs and outputs for each sector. When modeling airport economic flows, most studies begin collecting the raw data with a survey of each airport manager. That person provides the details of the airport spending which become the "direct impact" of that airport. The manager further provides a list of airport vendors and customers. Those firms are contacted, their industry is determined, and the portion of their spending, employment, and revenue attributable to the focal airport is collected which becomes the indirect impact. All of these observations are fed into one of the popular input-output models to develop an estimate of the "ripple effect" induced impacts across all the industrial categories, which are summed into an estimate of the total impacts. A sample airport manager survey is presented in Appendix 2. Some states also survey airport pilots and passengers and incorporate those expenditures into their economic impact studies.

Given that background and as noted above, this study argues that small general aviation airports should be measured by the economic impact each airport delivers to the communities they serve, as measured by input-output modeling techniques. Economic impact will be operationalized in three ways, and all three are available from the selected state-airport studies. First, the analysis will model the total payroll produced by the airport directly, indirectly, and by the induced effects. This variable will be measured in dollars. The second operationalization is the total employment attributable to the airport, which will be reported as full-time equivalent headcounts. Finally, the total economic impact of the airport will be modeled. This will be a dollar value and will be the sum of direct effects, indirect effects, and induced effects. These three factors will be used as the dependent variables in this analysis. This model is presented graphically in Figure 1.

Alternative Dependent Variables

There are other candidate variables for the operationalization of airport performance. One straightforward choice could be operational factors such as the number of passenger enplanements, the number of take-offs and landings (generically termed "operations"), the number and variety of services offered at the airport, or the number and types of airplanes based at an airport. Most of these items are reported to the FAA annually so the data is available, relevant, and reasonably accurate for all of the larger airports (usually, those with air traffic control towers). However, smaller airports have few incentives or mechanisms to measure these quantities precisely. Among the airports selected for this study, only 60 of the 235 airports had control towers. Because they are self-reported, inconsistently collected and

Figure 1. Graphical Representation of Hypothesized Model



poorly documented, operational data are sub-optimal choices for the dependent variable (for more details of the limitations of the operational data, see the discussion of FAA data in Chapter 4, below).

The recent development and deployment of web-based airplane tracking systems creates a new opportunity. Several businesses, such as FlightAware.com, synthesize data from FAA air traffic control radars and amalgamate it by airplane number, airplane type, departure point, destination point and many other options. The most sophisticated of these services enhance that raw data with a new technology known as Automatic Dependent Surveillance–Broadcast (ADS–B) tracking. These systems can track and analyze any flight by any airplane in the sky in real-time without the gaps caused by failures of radar coverage (in the U.S., the FAA's radar network is optimized for high altitude operations and is less reliable at low altitudes or in mountainous regions). If this data were available to researchers, these types of systems would enable accurate and detailed tabulations of aircraft operations at each airport. However, currently these systems have several deficiencies pertinent to this study. For example, FlightRadar24 focuses on commercial aircraft and simply does not show military or general aviation traffic. A competing service called ADS-B Exchange shows many more aircraft than FlightRadar24. FlightAware claims to be the largest aggregator of aviation data, but even their data shows gaps. This researcher owns a small airplane which flew three times in October 2022, but not one of those flights is found on FlightAware. In conclusion, while aviation data aggregators may improve over time, at this point including their data in the model seems problematic.

Another measure could be the profitability of the airport. Most municipalities and the FAA require each airport to be operated in a financially self-sufficient manner, and most facilities try to be profitable. However, as noted above, the vagaries of fund accounting make those numbers unstable. Additionally, as many airport budgets are buried in municipal financial reports, it may be difficult to cull the nuances of the airport's financial performance from those reports in a systematic and statistically reliable fashion. Of course, private airports are not required to provide any financial data at all, so there could be large gaps in the data set.

One final effort could be to conduct large-scale surveys of airport managers, seeking details of their operational performance, economics, and perhaps attitudinal indicators. While appealing in concept, the response rates may be low, the responses may be biased to the largest and best-run airports, and there may be a problem with social desirability bias among the respondents. Follow-up surveys may be useful tools for follow-on research in this area. Based on all the above, it is reasonable to conclude that economic impact as measured by the different states in their econometric studies are the best and most independent operationalization of the performance of a small airport.

CHAPTER 3. RESEARCH QUESTION AND HYPOTHESES

This research involves one simple question: to what extent does the organizational design of an enterprise effect the economic performance of that firm? The implications of a poor organizational fit ripple through an entire organization. As noted above, the employees directly tasked with running the airport will not be incentivized and intrapreneurship will not be rewarded. The search to find new markets, technologies and best practices will be deficient, and poor performance and resultant sub-optimal decision-making may continue for years creating the economic deserts found at many airports. These are difficult behaviors to manage, and if the organization neither recognizes, funds, enables or rewards these behaviors they will diminish. Since *operational control* touches each airport process, for better or worse the economic impact of the airport should reflect the congruence of the organizational design with the mission and strategy of the enterprise.

For the purposes of this study, the organizational design is operationalized as a categorical construct termed *operational control*. The dependent variable is the economic impact of the enterprise as measured by the economic impact studies of the three selected states. It is operationalized with three ratio-scaled variables attributable to each focal airport: total economic impact, total employment, and total payroll.

Specifically speaking to this empirical study, the research question is best stated as follows: all other factors being equal, does the degree of *operational control* available to the management team of a small airport enhance (or degrade) the ability of that airport to contribute to the economic health of its community? This could be generalized into broader terms such that organizations will enjoy greater success towards their goals when the supervisory structure of the organization is congruent with the day-to-day operational, technical, and financial requirements of the firm. Within the boundaries of this study, the specific hypotheses are:

- H1: The degree of *operational control* predicts the total economic impact of the focal airport.
- H2: The degree of *operational control* predicts the number of jobs created by the focal airport.
- H3: The degree of *operational control* predicts the total payroll impact of a focal airport.

It is anticipated that the *operational control* will also predict numerous operational decisions at a municipal airport. Specifically under conditions of a low *operational control* (a) there will be fewer airport services, (b) those services offered will be limited (e.g., self-service fuel versus full-service), (c) the physical condition of the airport buildings and public areas will be more basic and less ostentatious, (d) the airport manager will be less likely to have professional training in airport management, (e) the airport manager will be less likely to participate in airport association meetings and seminars, (f) airport employees will be less likely to engage in supportive voice behaviors, (g) both managers and employees will exhibit lower levels of job engagement, (h) the airport employees will be more likely to be represented by a labor union, and (i) the airport will have less independence in operational matters such as marketing, pricing, human resources, purchasing, payables, banking, legal representation, benefits, incentives, and compensation. These questions will require further research and richer data sources for their resolution.

CHAPTER 4. DATA & METHODOLOGY

The focus of this study is to model the drivers of the economic impact of general aviation airports. To improve the manageability of this study, a subset of those airports and the economic impact studies which describe those airports are the focus of this effort. In total, the study produced a dataset of 131 variables describing 235 airports in Florida, Virginia, and North Carolina. This section details the processes used to collect and organize that data. In addition, this section will explain the development of the control variables required for this study, the logic behind the selection of those control variables, and their segmentation into manageable "clusters."

Background: The Population of Airports and the Form 5010

A census of the aeronautical facilities reviewed in this study would include all the 20,002 facilities in the United States registered with the Federal Aviation Administration (FAA). This study involved the accumulation and integration of data from the FAA and other sources. The keystone of the project is the FAA Form 5010 report periodically filed by every airport in the United States. Formally known as the "Airport Master Record" the Form 5010 documents 76 different details about each airport in the United States. An airport inspector inspects each airport every three years for GA airports and annually for commercial airports. The findings of those inspections are memorialized in the Form 5010.

For example, while there are 13,247 airports for fixed-wing aircraft in the U.S., there also are 13 balloon ports, 36 sailplane bases, 6,059 heliports, 534 seaplane bases, and 113 facilities dedicated to ultralight aircraft. For each of those facilities, the FAA collects the name and contact details of the owner and the airport manager, its latitude and longitude, the airport elevation, the magnetic deviation, the date the airport began operations, the availability of

U.S. Customs and Border Patrol facilities, aeronautical services such as weather reporting, the different fuels available, and the availability of aircraft maintenance. It also requires the airport to report the number of aircraft based at the airport (by aircraft type), the number of operations at the airport (again, by aircraft type), and the presence of the airport on the NPIAS listing. Additionally, the form also collects secondary data about each runway at each airport, for a total of 23,860 landing zones. Each year the Master Record is published by the FAA in an Excel file.[8]

While the Master Record is comprehensive and highly useful, it is not without flaws. First, it does not document every landing facility in the country, merely those which some owner has decided to register with the FAA in order to be awarded an airport designation (for example, the "GNV" code for the Gainesville Airport). However, it is a reasonable assertion that any aeronautical facility with any significant economic impact is included in the FAA's roster.

A more serious problem stems from the fact that the data is self-reported by the airport, usually by the airport manager. Airport managers tend to be busy with operational chores and often lack a staff to whom they can delegate administrative tasks such as these. This means that while larger airports do an excellent job with their data collection, that degree of rigor is inversely proportional to the size and professionalism of the airport operations. For example, among the airports included in this study, 60 of those airports are supervised by a professional air traffic control tower. Trained experts monitor each flight and record aeronautical activity for a significant portion of each day (most airport towers do not operate 24-hours/day). This

[8] Source: https://www.faa.gov/forms/index.cfm/go/document.information/documentID/185474. Note that this data is password protected and access can be arranged via https://adip.faa.gov/agis/public/#/public.

data is highly trustworthy. Smaller airports also can, if they are motivated, deliver precise operational details. For example, Moore County (NC) airport reported exactly 136 military operations within the past year, tracked by a person sitting in an office adjacent to the runway every day, twelve hours per day. In fact, 130 airports submitted "exact" operational data, precise to the single digit, while 63 other airports (32.6%) submitted counts rounded to the nearest hundred. These submissions might be interpreted as "educated guesses" and the data should be viewed with some skepticism.

A third issue, related to the previous one, involves missing data. The FAA requests information on airport customers and traffic, segmenting the data by aircraft type (helicopter, single-engine, etc.) and mission (air taxi, commercial airline, general aviation, etc.). For many smaller airports this data is mostly guesswork, as many airports are unmonitored outside of normal business hours and many other airports do not collect this data in a rigorous manner.[9] Additionally, it is entirely possible that many airport managers do not appreciate the subtle distinction between answering "zero" and simply leaving the answer blank. For example, of the 20,002 landing fields in the Master Record a total of 11,307 airports reported the quantity of single-engine airplanes they had based on the field, including 720 which answered that zero single-engine airplanes were based at the field. That means 8,695 airfields are recorded with "missing" in the variable: about 43% of all the airports in the FAA system. As another example, in this particular study of 235 airports in three states, 42 airports had some degree of commercial airline service in the prior year. Of the remaining 193 airports, 44 reported "zero"

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[9] Traffic data is used as the basis for long-term capacity forecasts. In 2019, while assembling the data for a revised Master Plan for the author's local airport, the engineering company was surprised to discover the airport had exact data on aircraft operations by date, by aircraft type, by origin, and by aircraft registration number. The lead engineer on the project reported that for general aviation airports without control towers, "We never get data like this. Nobody else collects this kind of information." Source: private conversation with Paul Puszynski, Operations Manager at the Pinehurst Airport.

commercial service while 149 left the answer blank. As airline service was expected to be an essential control variable in this study, 149 missing cases would have degraded the power of the statistical analysis. In this case, the author was able to validate the presence or absence of commercial service and provide accurate data for all the airports in this study. But this type of correction simply is not possible for many of the other variables, and therefore the presence of a large number of missing cases became problematic with several of the analytical techniques described below.

Lastly, the Form 5010 filing may not be completely accurate due to omissions and/or oversights. In the case of the 235 airports included in this study, the author determined that 19 airports (9.1%) reported incorrect sponsorship information. The most common error was the failure to report that an airport authority was operating at the airport, as was reported at the Pinehurst (NC) airport, SOP.

The FAA Form 5010 report data was used for five critical groups or "clusters" of variables in this study, including: (a) the determination of the degree of *operational control* at an airport, as operationalized by the presence (or absence) of an airport authority or equivalent, which is the independent variable in this study. [10] The control variable clusters based on the Form 5010 are (b) the services available at the airport for pilots and planes, (c) the type and number of aircraft based at each airport, (d) the type and number of aircraft

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[10] To maximize clarity, this study will adopt the following protocol for constructs, clusters and variables. All constructs will be in lower-case italics. All cluster-names will be denoted in initial upper-case and enclosed in quotes. Each specific variable will be denoted in initial upper-case formatting with italics. All variable names begin with an abbreviation of the cluster to which that variable was assigned. If a variable is a nominal scale dummy, an upper-case "D" will be included in the variable name after the cluster designation. If a variable has been transformed by standardizing it the name will begin with a "Z." For variables which have been log transformed, the variable name will include the term "Log." For variables requiring catchment area specifications, they will be characterized using the variable name, in italics, followed by a distance measured in statute miles, e.g., *Cen_Population 15* or *Cen_Log_Total Income 30*.

operations at each airport, and (e) the competitive pressures on a focal airport by evaluating the type and length of all the airports and runways in the vicinity of each airport.

Other sources were used for the remaining control variables. These included the U.S. Census for data about the populations and income in the areas surrounding each airport, satellite imagery was used to evaluate land-use data around each airport, airport websites were explored in depth to develop a cluster of variables explaining airport governance, and the dependent variables culled from the economic impact studies produced by each state.

At this point, it would be informative to describe and explain each cluster of variables, the rationale behind them, the data included in them, and the data collection process. This study used 131 separate variables and, simply for ease of management, they were arranged into eleven separate “clusters.” The first cluster involves the independent variable(s). The second cluster is the decision-tree or “coding rubric”, used to create the independent variables.

The Independent Variable Cluster

The construct of *operational control* is envisioned as having three possible conditions: low, medium, and high. This cluster includes one string variable denoting all three conditions and three dummy variables for each possible condition. In an ideal world, implementing *operational control* as a ratio-scaled variable would be optimal, but the data simply does not yet exist. The airport-level FAA data does not include a measure of *operational control,* but it does have some information from which the construct can be inferred. Hence, a simple branching algorithm was developed to populate the independent variables. This rubric can easily be adapted by other researchers. The cluster is designated by the preface, “IV”.

The Coding Rubric Cluster

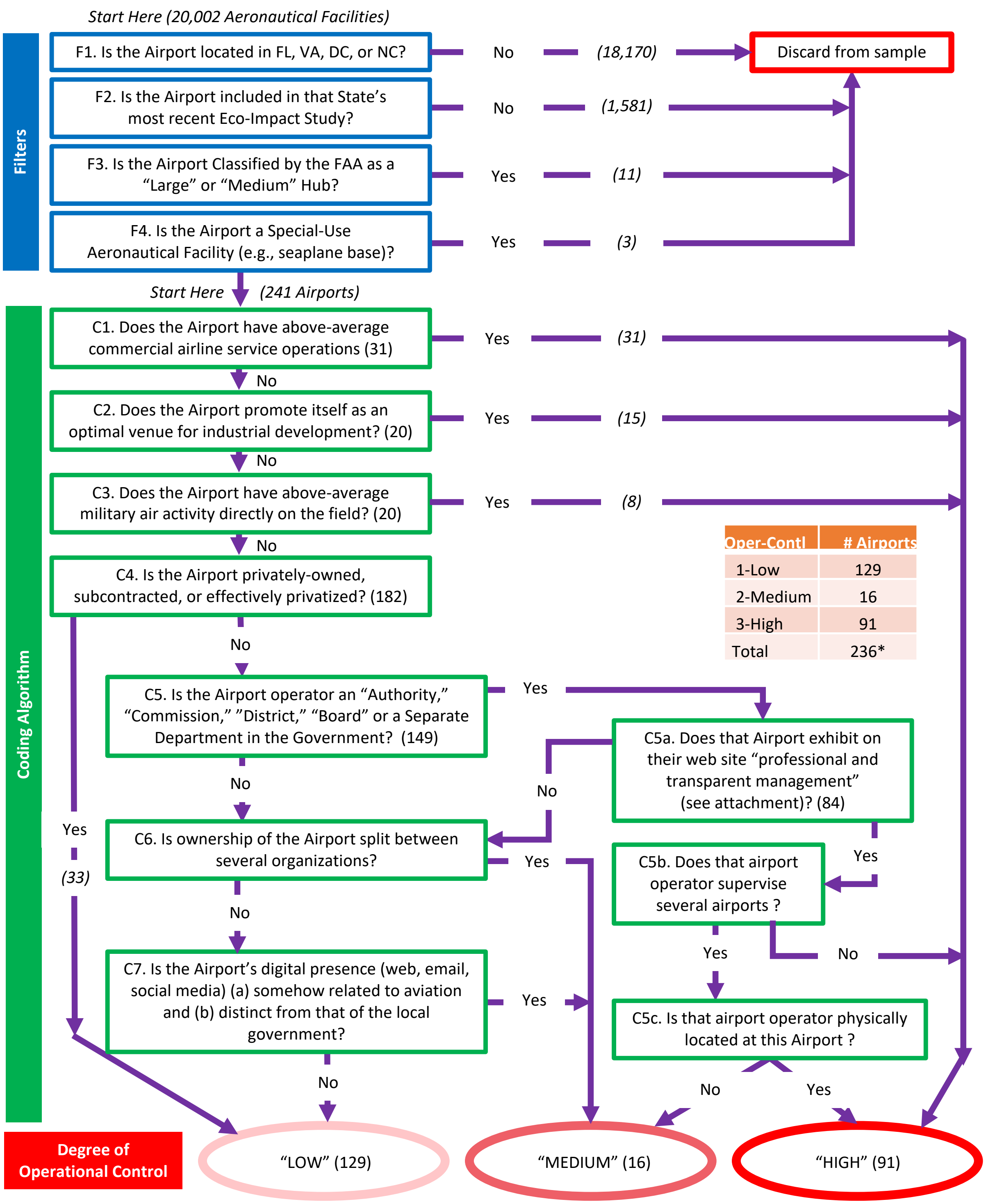
The coding rubric starts with four "filter" questions to exclude aeronautical facilities from this analysis. Then, ten yes/no categorical or "branching" questions were used to categorize the degree of *operational control* to be found at any focal airport. The following explanation explores the logic of the branching algorithm and is shown graphically in Figure 2. The answers to the categorical questions in the coding rubric were retained in the data set so future researchers can validate the algorithm and confirm the coding process. The raw data is in the variable cluster "Rubric."

Importantly, the coding rubric values were created without reference to the economic impact data, nor were they used in the statistical analysis as that would have induced a problematic degree of multicollinearity (in effect, a "circular reference" in the vernacular of spreadsheets). They are included here for completeness and for clarity for users who might be interested in the raw data itself.

Starting with questions C1 (Airline Service), C2 (Industrial Park) and C3 (Military Traffic), a positive answer to these three conditions automatically categorizes an airport as having a "high" condition of *operational control*. Airlines are for-profit entities with many more communities requesting their services than the airlines can accept. Airlines simply will not tolerate ineffectual results from their host airport management team. They will either abandon the airport or demand improvements from the legal owners. The same is true for airports supporting military operations, so it is reasonable to assert that airports with extensive airline service and/or military activity will, prima facie, have a high degree of *operational*

Figure 2:

"Operational Control" Filters & Coding Algorithm



* A total of 241 airports were selected for the final analysis. Five of those airports eventually were excluded from the study due to concerns about the accuracy of their self-reported data, leaving 236 airports. Later in the analysis, one additional airport was excluded as an outlier, although the data for that airport was considered accurate and true.

interpreted as the work of a diligent and energized industrial park can only be interpreted as a sign the airport management team is attempting to maximize the economic impact of the airport. This contrasts strongly with Question C4, "Is the airport privatized?" The privatization of an airport is the abrogation of almost all managerial responsibilities to a third party and can only be considered a symptom of "low" *operational control*. While any entrepreneur who buys hundreds of acres of land, builds a runway, and files paperwork with the federal government will certainly be motivated to do whatever it takes to have a successful operation, almost invariably a privately-owned airport will be impaired by the lack of both financial resources and professional management.

A condition of "high" *operational control* also is produced by Question C5 when the airport is operated by a "board", an "authority", a "commission", a "district", or operated as a distinct and autonomous department within a government. Approximately one-third of the airports in the panel have such an organizational structure. This means the airport operates as a single-function entity, separate and distinct from the confines of the municipal organization. In theory they also should be relatively free from the friction of ill-informed principals, allowing the airport to operate more effectively. However, the FAA data also shows there are several airport commissions in Florida which operate multiple airports. Without exception, every one of those commissions is located on the site of the largest of the airports. In this situation it is plausible, perhaps even likely, that the smaller airports do not receive the attention and focus they need. Distal and distracted management detracts from the ability of the smaller airports to achieve their full potential. In this situation the principal airport is assigned a condition of "high" *operational control*, but the subordinated, remote airports are assigned “medium” *operational control*. In this study, this condition was only observed in the state of Florida.

Question C6 distinguishes when the ownership of the airport is shared between several organizations. The FAA data indicates there are at least six airports in the sample with shared ownership, typically between two equal entities (two counties) or between a senior and subordinate entity (a county and a town). For example, the Surry Airport in North Carolina is jointly sponsored by the City of Mount Airy and Surry County. There are several airports in which the ownership is shared with Federal government agencies, such as the Nottoway Airport in Virginia which is jointly operated by the town of Blackstone and the US Army. The condition of “high” *operational control* is predicated on the assumption that the more energetic principals of one ownership team would over-rule ineffectual principals from the other ownership team. The more active and involved principals could be perceived as more willing to expend more resources in managing the airport while the ineffectual principal could shirk those duties with no penalty. While this assertion is tenuous, it is plausible that shared ownership results in a higher degree of *operational control* at an airport because it reduces the likelihood that an ineffectual principal would have strong sway over the operation.

The branching condition in Question C5a determines if the airport operates with some degree of freedom from ineffectual principals, as described above. While the FAA data is silent on this matter the internet offers a hint: the web site of each airport. In effect, Question C5a is an effort to operationalize the independence of the airports’ governance from city or county control. The question asked, “To what degree does the airport exhibit on its web site professional and transparent management?” This condition and the calculations behind it are more fully explained in the section below discussing the “Governance” cluster.

Continuing with the coding rubric: if an airport was routed to Question C7, one final effort was made to determine if the airport had even a modicum of independence from government control. Many of the airports in the study have discrete URLs which are aviation- or airport-related. Examples of these include @BocaAirport.com for the Boca Raton airport or @flyjax.com for the Jacksonville airport. Alternatively, many airports had emails, web sites and hyperlinks based on municipal governments URLs, such as "@umatillafl.org" for Umatilla, FL or "@hanovercounty.gov" for Hanover County Airport in Virginia. If not rated "high" earlier in this process, airports with aviation-related emails and web sites were rated as "medium" on the *operational control* spectrum.

The final step in the algorithm (Question C5c) required the physical address of the office of the manager of the airport, as listed in the FAA spreadsheet. Google Maps was used to determine if that address was on (or at least adjacent to) the focal airport. The intent here is to distinguish between those managers who might work at city hall and rarely deal with the airport itself from those managers who actively spent most of their hours on or about the airport. If the manager's address was on the airport, the airport was assigned a condition of "medium" *operational control*.

At this point, any airport not already assigned a code of "high" or "medium" was assigned the default condition of "low" *operational control*.

The Governance Cluster

The operationalization of the "professional and transparent" variable, Question C5a in the coding rubric, ultimately resulted in the creation of an additional cluster of variables, termed the "Governance" cluster. The development of this data required visits (and numerous re-visits) to all 241 airport web sites in the study. Working solely from the information discerned from each web site, twelve conditions or "behaviors" were observed and tabulated to produce thirteen new variables. The twelve item scores were calibrated as 0/1 categorical variables, along with a final thirteenth variable (*Gov_Engaged_Mngt_Index*) which was the sum-total for all the behavior-scores for each airport. Across the 241 airports, the scores for the variable *Gov_Engaged_Mngt_Index* ranged from zero to twelve. Fifty airports exhibited zero of the expected behaviors and one airport exhibited all twelve; the average for all airports was 3.10 behaviors. In terms of the coding rubric, the variable *Gov_Engaged_Mngt_Index* was used to resolve Question C5a; the variable was duplicated and renamed (*Rubric_C5a_D_EngagedGov)* into the Rubric cluster simply so the two groups would be consistent and complete. Airports with a score on this variable, *Rubric_C5a_D_EngagedGov* >=4 were classified as "yes" and those cases flowed to Question C5b (the value of four was selected because it was the first integer value greater than the mean). All other airports were classified as "no" and flowed to Question C6 in the coding rubric. The specific conditions are summarized and explained in Figure 3.

It would not be unreasonable to question the validity of this tabulation. It is, after all, an effort to quantify a latent management attitude — "professional and transparent" — with a technically distant marketing tool deployed by the airport. However, personal experience suggests this construct is a reasonable proxy for professionalism, energy, customer service and transparency. It takes a great deal of initiative, self-awareness, sustained focus, and funding to create and maintain an informative aviation web site. The willingness to make this investment can be judged as a direct manifestation of degree to which the airport management team is committed to serving its customers. That commitment can only be produced in an environment with strong and continuous support from the top of the organization. If an airport

Figure 3:

Operationalizing "Professional and Transparent" Airport Management Using Each Airport's Public Web Site
(Rule C5a of the *Operational Control* Coding Rubric)

A "professional and transparent" airport sponsor demonstrates diligent governance of their airport by deploying some or all of the following behaviors. All twelve behaviors are categorized as binary "yes/no" results. For example, Item 2 considers if the web site has been recently updates. Finding even one recently updated page results in the site being rated as "updated." The name of each variable is presented in brackets [ ]. These variables all are included in the Governance ("Gov") cluster.

1. There is a unique airport web site, not just a page in the owning organizational web site. [Gov_Unique Website]
2. Some portion of the site has been updated within the past year. [Gov_Recent Update]
3. Team members identified (authority members or airport employees are both acceptable) [Gov_Team Named]
4. Team members profiled and have relevant aeronautical expertise, including items such as the dates of terms or constituencies represented [Gov_Team Profiles]
5. Contact info listed (individual emails, not snail-mail) [Gov_Team Email Info]
6. Aviation- or airport-oriented emails (e.g., joe@myairport.com) are used, not ".gov" email addresses [Gov_Aviation emails]
7. Airport Authority schedules listed [Gov_Dates Pub'zed]
8. Meeting minutes published in a timely manner [Gov_Minutes Pub'd]
9. Airport documents available (e.g., Master Plan, ALP, forms to rent hangars, standards, and other regulations) [Gov_Airport Docs]

# of Behaviors Demonstrated	# of Airports
0	50
1	31
2	42
3	32
4	23
5	9
6	8
7	19
8	9
9	8
10	4
12	1
Grand Total	236
Average, all airports:	3.10
# Above Average:	84

10. Newsletters, press releases or stories of activities at the airport are on the site [Gov_PR or Newsletters]
11. The web site actively solicits airport-related business opportunities which improve economic impact of the airport [Gov_Solicit Business]
(Special note: This rule specifically excludes website advertising about airline terminal services that airline passengers might use. Instead, this behavior is a measure of the effort an airport expends to recruit non-airline industrial businesses.)
12. The web site encourages visitors to explore the community: famous sites, history, restaurants, hotels and events [Gov_Cmmty Engaged]
(Special note: This rule specifically excludes passive links to other web sites such as the local Chamber of Commerce. It requires original content on the airport web site.)

single and uninformative page buried in a governmental web site. In contract, in a condition of "high" *operational control* the web site will offer a broad array of airport information, employee profiles, contact details and governance information. Table 4 quantifies this hypothesis and validates the conclusion that airport web sites can be interpreted as a slightly blurry reflection of the energy, diligence and transparency of the airport management. The raw data is collected in the variable cluster, "Governance."

Airport Catchment Areas

Another element in this analysis was the determination of the optimal "catchment area" for each airport. It is common in econometric studies to use catchment areas as a planning tool. Originally used by geographers to document the flow of rainwater into streams, rivers and lakes, the term has expanded to be geographic area (as measured by distance, time or some other degree of effort) surrounding a focal institution, such as a museum or store, from which it attracts a population to use its services. Governments often use catchment area planning to ensure suitable access to public services[11] such as fire departments, bus services, outreach to the homeless[12], etc. For example, a retail store location analysis might begin with the knowledge that majority of customers of similar stores live within one mile of a store location, so the catchment area would be described as a circle with a one-mile radius.

Selecting the optimal catchment area for an airport is a challenge (Findley *et al.,* 2021) and there is no literature known to this author describing or quantifying the optimal catchment area size for small GA airports. For large commercial airports, catchment areas are measured with radii of hundreds of miles. They are defined by proximity to other competing airports,

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[11] Source: https://en.wikipedia.org/wiki/Catchment_area#Defining, on Sept. 21, 2022
[12] Source: https://opendata.dc.gov/datasets/DCGIS::human-services-catchment-area/about, on Sept. 21, 2022

driving times, the number of served destinations, flight frequencies, fares, and the availability of nonstop services (NASEM, 2009). A key component of the catchment area discussion is access, so reliable public transit or four-lane highways expand catchment areas while limited rural roads or impassable geographies shrink them. Other constraints may be international borders, the nature of the market (business travel versus travel related to family and cultural ties), the presence of an airline hub and/or the availability of competing airports (NASEM, 2013). As a point of reference, a 30-mile catchment area encompasses 2,827 square miles, bigger than the state of Delaware. One of the secondary goals of this study was to determine, to the extent possible, the optimal catchment area size for general aviation airport research. The Census cluster, the Geography cluster and the Competition cluster, all described below, use catchment area definitions.

The Census Cluster

It is plausible that the economic impact generated by an airport could be enhanced or degraded by the demographics of the region and the relative prosperity of the surrounding community. Prior literature has cited demographic and economic data such as the catchment area population, per capita income, and employment growth. These links have been clearly documented. For example, in the NASEM (2009) report, for every additional $5,000 in per capita income, a community had 3.3 more jet departures per week and for every additional 25,000 jobs, a community had 4.3 more jet departures per week. It is reasonable to expect that there are fundamental and direct relationships between population and the aeronautical activities a community can support.

For most demographic research, the U.S. Census represents the gold-standard in both the breadth and the depth of the data collection and analysis. The Census is required by the U.S.

Constitution and is used to re-apportion the seats in the House of Representatives, assist redistricting efforts, and provide data to calibrate the provision of funds and grants to communities for new roads, hospitals, schools, and other public functions. The most recent census was in 2020 and published on September 16, 2021[13]. Every household in the country received multiple invitations to participate which produced a non-response rate of less than 0.52% overall.[14] With an annual budget exceeding $1.5 billion, the Census Bureau can supplement the decennial census population and business data with 130 smaller surveys, programs and statistical models. The Bureau publishes more than 2.5 million tables of raw data, maps and profiles. Since census data is available in time-series format, it becomes a key source of information about changes in the U.S. population and the evolving needs of the citizenry.

The most granular data in the census is reported at the level of the "census block." In 2010, there were 11,155,486 census blocks in the United States. Census blocks typically are defined by roads and highways, political boundaries, or easily observed natural features such as rivers. In densely populated areas, a census block may be a city block; a large apartment complex might comprise a census block by itself and have several hundred inhabitants. Census blocks are larger in rural areas. In the 2010 census 4,871,270 census blocks reported a population of zero.

Since managing the enormous scope of the census data is a challenge for all but the most expert users, private vendors "repackage" the census data into more user-friendly formats.

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[13] General information about the U.S. Census was sourced from the official Census web site and Wikipedia and is included here to clarify the operationalization of the control variables.
[14] Sourced from the U.S. Census on Feb. 7, 2023 at: https://www.census.gov/newsroom/blogs/random-samplings/2021/08/2020-census-operational-quality-metrics-item-nonresponse-rates.html

This study used data from the "2016-2021 American Community Survey" retrieved via a commercial service called SocialExplorer. SocialExplorer has a graphics and analysis package which allows users to interact with the census block data to create customized reports, maps, and charts. It also integrates data from other sources including the United States Bureau, the FBI, The World Bank and Eurostat to produce literally hundreds of thousands of indicators related to demography, the economy, health, politics, environment, and crime. The SocialExplorer software aggregates the census data to match user needs which were, in the case of this study, circular catchment areas with radii of 15 miles, 30 miles and 50 miles around each airport in the study. If a catchment area boundary included only a portion of a census block, the software automatically averaged the population, employment, and income data within that census tract proportionately (that is, the data within a census block is assumed to be homogenous). The data was collected for the author by an expert in the SocialExplorer geographic information system from the Institute for Transportation Research and Education, which is part of the North Carolina State University. Three catchment areas were defined as described above (15-, 30- and 50-mile circles), creating nine census observations for each of the 241 initial airports.

In terms of the specific variables, the census data included the population of the catchment area, the total income of all persons in the catchment area, the total employment within the catchment areas, and total civilian employment within the catchment areas. The census reports employment in two forms: with and without military employment in the census block. It was noted the difference between these two employment figures varied significantly from airport to airport. Since it is well-known that the presence of the military increases the economic impact of an airport it was reasonable to retain that extra variable in the study. This data allowed the computation of indices and interaction effects such as the population density. In the data file, the cluster is prefaced with the term “Cen” (Census).

The Geography Cluster

It is plausible that the economic activity of an airport can be shaped by geography in several different ways. For example, Danbury, CT (DXR) is an airport nestled in a deep valley surrounded by steep terrain. Because of this condition, Danbury will never be acceptable for commercial airline service which, in turn, minimizes that airport’s ability to generate outsized economic impacts.

Satellite-derived land-use data is a relatively new technique to operationalize geographic data in econometric studies. It has been made possible by advances in commercial satellite technology, remote sensing technology, networking speeds and computer power. In terms of this study, the geographic information was operationalized using high-resolution satellite imagery available from the Multi-Resolution Land Characteristics Consortium, sponsored by the Earth Resources Observation and Science Center which is part of the U.S. Geological Survey (USGS). The USGS has, in partnership with several other federal agencies, released triennial National Land Cover Database (NLCD) databases. After an initial release in 2001, the data has been updated seven times, most recently in 2019. These files provide detailed and reliable information on the geography, land cover and land usage within the United States. Using Landsat imagery and other sensor technology the latest iteration (NLCD 2019) provides consistent and integrated data from a variety of multi-temporal sensors which can operate at night, through clouds or even through forest canopies with a published resolution of 10x10 meters. The system categorizes surfaces into eight major categories with sixteen sub-categories. For example, aqueous surfaces can be coded as either “open water” or "perennial ice." There are four categories of development, three types of forests and two types of farmlands. Each pixel in the database covers a 30x30 meter square. According to NLCD, the system has an overall accuracy of 91% for overall landcover classification. An annotated example of the NCLD output is included in Appendix 3.

Economic activity is somewhat independent of population; substantial economic activity can occur even in areas with relatively small populations such as when a giant Amazon warehouse opens in a rural setting. Two geographic variables were considered most relevant. The first of these was the extent to which the catchment area had been developed for economic activity in the 2019 satellite images. This was operationalized as the square miles of surface area within each catchment area of the airport covered by any of the four categories of impervious surfaces (e.g., buildings, highways and roads, rooftops, parking lots or garages). (A secondary variable, the change in impervious coverage in the past twenty years, was collected but reserved for future analysis.) The relationship was conceived to be linear.

The second geographic variable was conceptualized as the extent of unusable surfaces in the catchment area. Unusable surfaces were operationalized as the square miles of surface area covered by navigable waters. It was considered likely to be a negative quadratic (inverse concave) function using a "diminishing returns" model. Consider the fact that waterfront properties are generally highly desirable. People will be attracted to areas where waterfront property is relatively abundant, and so an airport in that region potentially will be more affluent and will have the opportunity to produce proportionately greater economic impacts. This trend continues until the geography is mostly water and unable to support significant economic activity. A small island airport, for example, will have a reduced ability to produce a substantial economic impact for its community.

The satellite land-use data was collected for the author by the same GIS expert at the Institute for Transportation Research and Education, a center at the North Carolina State University. The data collected was for all three catchment areas for all the airports in the three states. Since the area of a catchment zone is a constant (a 15-mile catchment zone encompasses 706 square miles) the manipulation of the two variables and the 706-sq. mi. constant enabled the construction of other index variables. These included: (a) the total possible buildable area in the catchment zone (which is a measure of market potential), (b) the proportion of land already developed, (c) the square miles of land remaining available for development, and (d) the "economic intensity" of the catchment area, which used both satellite data and census data. Specifically, the economic intensity of a catchment area was computed as the total household income of all the homes in the catchment area divided by the square miles of impervious surfaces in the catchment area.

The final geography variable is inherent to aviation: people use planes to go places. It is well-known in the industry and documented in the economic impact studies that airports benefit from their proximity to prominent destinations, such as Hilton Head resort or Disney World (NASEM, 2009). For example, the Arizona (2017) economic impact study includes numerous tourist attractions, including the Phoenix International Raceway (PIR), the Barrett-Jackson Collector Car Auction every January, the Super Bowl, and an annual professional golf tournament. South Dakota (2020) includes specific data about the annual Sturgis motorcycle rally which attracts 500,000 visitors. These events and destinations generate traffic and economic impact over and above the efforts of the management team at the airport. Operationalizing this ambiguous construct was a challenge and was resolved by using

TripAdvisor.com to develop a list of iconic destinations for each state and then Google Maps to measure the highway distance from each airport to that destination.

Unlike some of the economic impact studies cited above which included short-lived events or seasonal attractions, four robust criteria were used to define an iconic destination. To qualify in this study, such a destination had to be a (a) world-recognized attraction, (b) permanently located, (c) operating year-round, and (d) not a beach resort. (This last detail was included because the impact of water-front attractions was captured in the variable measuring surface areas covered by water, described above.) The final list of iconic destinations is included as Table 4. The distance in statute miles to the nearest iconic destination was used as the observation for each airport. It is possible that an airport might serve two or more equidistant iconic destinations but, in the 241 instances explored in this study that condition was never observed.

As a minor note, also included in the Geography cluster are a few items derived from the FAA Form 5010 report, including the distance (in miles) to the central business district and the elevation of the airport above sea level. In the dataset, all the relevant variables are prefaced by the term “Geo” to indicate the Geography cluster.

The Competitive Cluster

Airports are not isolated islands but could act as competitors to each other, enhancing or degrading an adjacent airport’s economic performance. One possibility is that neighboring airports could stimulate activity at the focal airport; companies and people would be aware of the advantages of aviation and be comfortable with the processes and costs. Alternatively, an equally plausible hypothesis could be that the presence of busy competing airports might be

Table 4:

Iconic Destinations in Florida, Virginia and North Carolina

State	Destination	Visitors/year*
Florida	1. Disney World	59.30
	2. Kennedy Space Center	1.50
	3. Miami Beach Historic District	24.20
	4. Everglades National Park	1.00
	5. Historic Key West	5.10
	6. St. Augustine Historic District	6.30
	7. Pensecola/Panama City Beach District	4.50
Virginia	1. Washington DC Area	18.80
	2. Williamsburg/Jamestown	1.50
	3. Shenandoah National Park and Skyline Drive	1.00
	4. Mount Vernon	1.00
	5. Monticello	0.50
	6. Luray Caverns	0.50
	7. Richmond/Petersburg Historic District	7.00
North Carolina	1. Great Smokey Mountains Natl. Park	14.20
	2. Cape Hatteras Beaches & Lighthouse	2.61
	3. Pinehurst Golf Resort	1.14
	4. Biltmore Estate, Asheville	1.00
	5. Wright Brothers Memorial	0.48
	6. Grandfather Mountain	0.30
	7. Battleship No. Carolina, Wilmington	0.25

** Visitors per year in millions.*

detrimental to the economic health of an adjacent airport as competitors pirate away traffic and business activity.

To test these conflicting possibilities, the FAA runway database of 23,000 facilities was scoured for information about available airports and runways in the 15-, 30- and 50-mile catchment areas around each focal airport (NASEM, 2009). For each airport and for each catchment size, three variables were created: (a) a count of the number of airports in the catchment area, (b) a count of the number of runways in the catchment area, and (c) a summation of the total length of all the runways in the catchment area, for a total of nine observations for each focal airport. The underlying premise of this analysis is that more runways imply greater aeronautical activity, more runways offer more options in inclement weather, and longer runways offer more opportunities than smaller ones.

Two independent programmers were hired and were provided the FAA data files; the output files would be compared to validate the accuracy of the coding. Each programmer independently created their own computer code to parse the airport and runway data from the FAA Form 5010 report. The computation of distances was based on the Haversine formula for converting latitudes and longitudes into linear distances.[15] Four "filters" were used to define airports and runways as competitors to any given focal airport: (a) the competitive runway must be in the catchment area of the focal airport (either 15-, 30- or 50-miles), (b) the runway must be 2,000 feet or longer, (c) the runway must be made of asphalt or concrete (no turf runways or seaplane bases), and (d) the runway must be available for public use (i.e., not a military airport or burdened with some other restriction).

Two nuances of this filtering process are worth noting because it added runways and airports not included in this study. First, it is possible for airports to have competition from airports in other states. This occurs if both the focal airport and the competitive airport are near each other but on opposite sides of a state boundary. Since competition doesn't stop at a state line, this condition was permitted. As an example, the large airport in Martinsburg, West Virginia along with two other Virginia airports are within the 30-mile catchment area of

[15] For more details about the Haversine formula, see: https://www.sisense.com/blog/latitude-longitude-distance-calculation-explained/

Winchester Regional Airport in Virginia. While this study did not model West Virginia airports, the characteristics of that airport was included in the calculation of competitive effects.

Second, large NPIAS "hub" airports (and their runways) were not modeled in this study but could be considered as competitors. As one example of this, Orlando International was not modeled in this study but appears as a competitor to seventeen local aerodromes.

One of the problems with this task facing the programmers was that it was impossible for the programmers to validate their coding without access to aeronautical maps or flight planning software. The correct answers for a half-dozen airports (two in each state) were manually computed using flight planning software for the programmers to use as a validation tool. Two problems arose. First, flight planning software reports distances in nautical miles, so the catchment areas created by the flight planning software were 14% larger than the catchment areas created by the programmers and occasionally included airports that the programmers excluded. Second, there were several instances in the FAA database where the precise latitude and longitude data for the runway(s) were missing. After discussions with the programmers, it was decided to substitute the airport's latitude and longitude data in place of the runway data because 100% of the airports had longitude and latitude information. The results were provided back to the author in an excel file.

To further test and validate the competitive data, off-the-shelf flight planning software was used. In effect, a flight was "planned" from the focal airport to every airport in the catchment area. This created a "starburst" of flights centered around the focal airport. The flight planning software also measured the length of each "leg" of such a flight, and the graphical interface allows users to visually inspect for outliers. Appendices 4a, 4b and 4c shows one such test, for Louisa County Airport in Virginia just outside of Washington, DC. Approximately twenty airports were tested and confirmed the aggregation of the competitive airport data for all three catchment areas was computed correctly.

The Services Cluster

For the purposes of this study, airport services were defined as technical capabilities or operational features of the airport reported in the FAA Form 5010 report (and occasionally corrected by the author, based on information from the airport's web site). Eight such services were judged to be most relevant to the economic impact of an airport: the age of the airport, the number of runways the airport operates, the length of the longest runway, the material of construction used in that runway, the presence of air traffic control tower, the presence of U.S. Customs & Border Patrol facilities, the presence of an out-sourced aircraft service center (termed a "Flight Base of Operations" or "FBO"), and the inclusion of the airport in the FAA's list of important airports, termed the National Plan of Integrated Airport Systems (NPIAS).

The turf runway variable may puzzle some readers. During the data preparation process, it was discovered that seven airports included in the Florida economic impact study were facilities with only turf runways. This could qualify the airport as a "special use facility" and expel it from the study. Upon reflection, and since the Florida Dept. of Aviation felt the airport was of sufficient economic importance to include in their study, those airports were retained in this analysis. However, a turf airport obviously has constraints on the economic impact it can generate, no matter how energetic the management team might be. Because of this condition, a special categorical variable was added to accommodate the turf-runway situation and the analysis was conducted both with and without the turf runway airports, to explore their effects.

The age of the airport was considered a potentially useful control variable under two hypotheses. First, it was thought plausible that older communities and older airports would have had decades to build greater economic benefits from the presence of each other. Second, a large number of airports were built during World War II, especially in Florida. Many of those airports have three runways — an expensive investment rarely seen at more modern facilities. It is plausible that the unusual quantity of infrastructure at older airports might create an advantage over a newer but simpler facility. The availability of local air traffic control services (“ATC”) is an important boost to all-weather operations and overall safety, so it seems plausible that could have an effect on economic impact. While the availability of Customs facilities is obviously a significant factor at the largest commercial airports it also can be very important to those GA airports adjacent to national borders, such as near the Bahamas and the Caribbean. The presence of an out-sourced FBO can be both detrimental to the airport’s economic impact or an enhancement. If a small airport is operated by a distal management team such as a local government, it is easier and cheaper for management to farm-out the greeting and fueling of airplanes to a commercial vendor. On the other extreme, the busiest airports often contract with multiple professional FBO providers to serve customers because those companies may deliver a higher level of service and offer competing services than the airport could do by itself.

The last Services variable is a dummy variable denoting the inclusion (or not) of the airport in the FAA’s National Plan of Integrated Airport Systems (NPIAS) and this variable is worthy of some explanation. The FAA has created the NPIAS to identify those public-use airports that have the potential to significantly contribute to the function, safety, resiliency and efficiency of the overall national airport system. The NPIAS includes approximately 3,300 facilities and features all commercial service airports, all reliever airports, and selected public-owned general aviation airports. The NPIAS roster memorializes the roles those airports currently serve and categorizes any planned airport improvements eligible for Federal funding. The FAA reviews and updates the NPIAS roster biannually. NPIAS airports are likely to be better equipped, more professionally managed, and have greater capacity than non-NPIAS airports. For example, none of the airports in the NPIAS system have primary runways made of turf. All of these variables are in the dataset with a preface of “Serv.”

The Based (Aircraft) Cluster

The Form 5010 filing includes information on the number and types of aircraft permanently housed at any given airport (generally termed, “based aircraft”). Every flight-worthy aircraft in the U.S. is required to be registered with the FAA in a process similar to an automobile registration. The airport manager is required to annually update the roster of locally-based aircraft using an FAA subsystem called the National Based Aircraft Inventory Program. This is accomplished on-line at BasedAircraft.com, an FAA web site. The FAA processes this information for a number of different projects including the Form 5010 report. For the purposes of this study, eight base variables from the Form 5010 report were included: the number of single-engine aircraft, multi-engine aircraft, jet-engine aircraft, helicopters, sailplanes (also called gliders), ultralight aircraft, military aircraft, and a grand total of all based aircraft. It is notable that many of these categories overlap. For example, most jet aircraft are multi-engine aircraft, and many helicopters are jet-powered, so double-counting is a concern. The preface for these variables is “Base.”

The Airport Operations Cluster

The fundamental duty of an airport is to facilitate aircraft operations. The FAA Form 5010 documents the number of take-offs and landings each year at each airport, subject to the weaknesses mentioned above. For the purposes of this study, seven categories of operations[16] were considered most useful: the total number of operations, the number of general aviation operations generated by airplanes based at the focal airports, the number of general aviation operations generated by transient airplanes (that is, not home-based at the focal airport), the number of "air taxi" operations (charter flights), the number of military flights, and the number of airline flights. The preface for these variables in the dataset is "Ops."

The Dependent Variable Cluster ("Economic Impact")

The economic impact data was sourced from the detailed economic impact reports of the states of Florida, Virginia, and North Carolina, as mentioned above. In all three states, the data was published in tabular form and imported into a spreadsheet. Each record was uniquely identified by the airport identifier code, which is the familiar three-letter code used on airplane tickets and baggage tags (e.g., "GNV", "RDU"). These codes were developed and are managed by International Civil Aviation Organization (ICAO), a division of the United Nations, and are unique world-wide. The use of the ICAO identifier ensures a perfect and unique match between different data sets.

As is typical with these types of studies, each state's report was slightly different, depending upon the goals of the originating agencies. Not all the studies reported the details of the subordinate measures of economic impact, and some studies reported additional details

[16] It is important to recall that, as noted earlier, an operation is either a take-off or a landing, and every successful flight generates two operations.

like visitor spending and taxes paid at each airport. However, all three studies delivered consistent measures of economic impact: payroll (in dollars), employment (number of persons working because of the airport's activities, reported as full-time equivalent headcounts), and total economic impact (the sum of direct effects, indirect effects, and induced effects, in dollars). As noted previously, these three items were used as the dependent variables in this analysis. The preface for the dependent variable cluster is "DV."

Data Cleansing: Economic Impact Study Availability & Comparability

Early in the development of this study, consideration was given to selecting a nationwide random sample of all the airports for which economic impact data was available. The allure of that design is clear: sample sizes could be larger, and generalizability would be more robust, thereby enhancing the validity of the study. Ultimately, detailed reviews of the different state studies found numerous procedural, econometric and temporal inconsistencies which would make a random design sub-optimal. The decision was made to limit this analysis to a small selection of highly comparable studies.

The oldest report is from 2003 (Nevada) and the most recent one is from North Carolina (2022); there are two other recent publications from 2021 (Vermont and West Virginia). There have been many economic, social and technological changes in those two decades which would make comparing the studies difficult. Geography and economics play a factor as well: among the states with eco-impact reports, Alaska (2019) and Texas (2020) have the most airports while compact New Hampshire (2013) has the fewest. Nevada (2003) has the lowest GA economic impact at $368 million while Florida (2019) has the greatest economic impact at $162 billion, a degree of variance which might make comparisons difficult. Other studies included tax revenues as part of the "economic benefit" the community derives from the airport (Massachusetts, 2019; Maryland, 2018). Some airport economic impact studies included seaplane bases (Alaska, 2019; Florida, 2019; Washington, 2020) while others included airports with turf or dirt runways (Alaska, 2019; Idaho, 2020; Oregon, 2016) which was justified because those states rely heavily on hunting and fishing tourism. Florida (2019) and Arizona (2017) both included military airports in their study; Arizona also included a special sub-study on aviation training, because so many flight schools are in that sunny state. South Dakota (2020) included specific data about the Sturgis motorcycle rally, Idaho (2020) included data from aerial forest fire fighting and New Hampshire (2013) included the economic benefits of the Alton Bay ice runway which is located in a cove on Lake Winnipesaukee and only available during the winter months.[17]

It also was important to find economic impact studies in which no single airport overwhelmed the data. Two cases are pertinent: Delaware (2018) has only nine airports in their analysis, which limits the statistical power of any analysis. In Georgia (2019) the huge Hartsfield-Jackson Atlanta International airport accounts for 90% of all the aeronautical economic impact in the entire state. Including either Delaware or Georgia in this analysis would be problematic.

The FAA-approved IMPLAN econometric model was used in 26 studies but even within those reports there were non-trivial variations in the way the model was deployed. For example, there were significant state-by-state variations in the rigor of the survey data collection process at the heart of the economic impact model.

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[17] Perhaps unique in the United States, the Alton Bay Ice Runway (B18) is a state owned, public-use general aviation airport with a runway made of ice. It is located in in New Hampshire about two miles north of the town of Alton. The airport is an ice runway during the winter and a seaplane base in the summer. During the winter, Runway 01/19 is plowed and marked as 100’ wide and 2,600’ long. A parallel ice taxiway and an aircraft ice parking apron are also provided. No aircraft are based at B18. Operations over the winter months average about 600 operations, fluctuating due to weather conditions and availability of sufficient ice.

Upon reflection, the data collection filter was finalized to limit the study to just a few states with enough airports for meaningful statistical analyses while minimizing the variation stemming from both documented and undocumented procedural differences in the state study methodologies. It was concluded that the Florida (2019) economic impact study would be an optimal choice for this analysis. The Florida Department of Aviation conducted a recent replication of their triennial economic impact study to quantify the impact of the extensive aviation system within that state. That study covers 20 commercial service airports and 109 public-use general aviation airports, so the sample size of 129 is moderately robust. No single airport dominates the region, no specific industry overwhelms the others, and no localized effects such as a motorcycle rally warp the data. Indeed, Florida's airports support a wide array of industries, including tourism, agriculture, space, manufacturing, medical services, law enforcement, search and rescue, and disaster response. Statewide, the total economic impacts of these airports boosted Florida's economy by nearly $162 billion in 2019.

The best methodological design requires the theoretical model to be applied to the data without *a priori* information or insights as to the patterns in the data. However, any study requires making difficult decisions about the specific constructs in the analysis, including the operationalizations of the constructs, the measurement scales, units of measure, transformations, handling of missing data, the optimal accommodations for outliers, and other factors. After reviewing all 42 U.S. economic impact studies (the three international studies were excluded) two additional studies were selected as validation tests of the statistical models. The studies produced by the states of Virginia (2018) and North Carolina (2022) were found to be most comparable. All three states were roughly comparable in size and economic vigor, all three had vibrant aeronautical economies, all three economic impact studies were relatively recent, all three were in the southeastern part of the U.S. so weather would not be a major source of variance, all three used the IMPLAN input-output model, and all began their analysis with a survey of airport managers followed by surveys of airport-based employers and airport visitors. Appendix 1 provides the complete list of studies, including those excluded from this analysis.

Data Cleansing: Non-standard Aeronautical Facilities

The second step in the data cleansing process was developing a filter to remove from the state reports those unusual airports which industry knowledge suggests could cloud or distort any findings. Three rules fit this requirement. First, this study excluded any military airport, NASA facility, or federal or state facility which are not open to the flying public; one example would be aerial fire-fighting airports. As mentioned above, military airports do not use traditional business models, their performance measures are very different, and their operational data are not available to the public. As a matter of comparison, the Jacksonville Naval Air Station was removed from this study while Eglin Air Force Base — a joint-use airport in the town of Fort Walton Beach in the panhandle of Florida — was retained because it offers commercial air service to civilian traffic.

There are “special use” airports in each study which were removed. Specifically, the FAA data shows there are two balloonports, seven ultralight ports, four sailplane ports, 640 heliports, and 64 seaplane bases across the three states in this study. In the Florida study, economic impact data was reported for three special-use heliports and seaplane bases. Because (a) they are so very different from traditional airports and (b) the economic leverage they can contribute is constrained by their unusual operations, those locations were excluded from the study.

One additional group was purged from the data. Commercial airlines only serve 493 airports in the U.S. The largest civilian airports are enormous and autonomous enterprises, with professional managers, large budgets, sophisticated engineering teams and complex information systems. Commercial airports are classified by the FAA by the intensity of their commercial networks and are rated as "large," "medium," "small" or "non-hub" airports. The "large" and "medium" hub airports were excluded from the study because they are massive economic ecosystems in their own right. It is likely that in an econometric analysis inclusive of their data would suffer from outlier effects which would overwhelm the more nuanced variances in the data of the smaller airports. The following large or medium hub airports were excluded from this study: Fort Lauderdale/Hollywood Intl., Jacksonville Intl., Miami Intl., Orlando Intl., Palm Beach Intl., Southwest Florida Intl. and Tampa Intl. in Florida, Charlotte/Douglas Intl. and Raleigh-Durham Intl. in North Carolina. No airports were excluded in Virginia because Reagan-Washington National and Dulles International both are classified by the FAA as being in the "state" of Washington, DC. As a matter of comparison, the Gainesville, FL airport is classified as a "non-hub" airport while Panama City, FL is a "small" hub; both of those airports were retained in this study.

In summary, this analysis evaluated 241 fixed-wing airports across three states, using data collected from 2016 to 2022, and organized according to the FAA approved IMPLAN model. After examination of the data, six airports were deleted as outliers leaving a final study cohort of 235 airports.

CHAPTER 5. ANALYTICAL PROCEDURES

Using OLS regression techniques and the SPSS statistical package, this study examined the degree to which an airport — or any organization in which ownership and operations are geographically, socially, economically and/or politically separated — could use an optimal organizational design to out-perform its peers. In the case of small airports, this was accomplished by using non-traditional non-aeronautical measurements. After the data collection, exploration and coding described in Chapter 4, this analysis proceeded with five steps: (1) the unification of the data into a single dataset, (2) any data errors, outliers and leverage observations discovered and removed, (3) the parsimonious development of transformations, conversions, and indices, (4) the statistical analysis, and (5) reporting and documentation.

Data Integration into a Unified Dataset

All seven sets of data were organized using the unique three-letter airport identifier (e.g., “RDU”, “GNV”). Using that airport identifier as the key field for organizing the separate databases, a programmer was hired to merge the distinct datasets into one large file which was accomplished using the SAS statistical package. The final package file contained 131 data points on 241 airports in three states. A validation check was performed by examining twenty randomly selected airports and comparing the data values. No errors were discovered. At this point, a general exploration of the airport data was undertaken to better understand the patterns in the data and look for outliers or leverage cases. Tables 5a describes the general descriptive statistics for the salient ratio-scale variables in the analysis while Table 5b describes the frequencies of the principal categorical variables in this study.

Data Exploration

It is useful to briefly describe the finished dataset. Of the 131 variables, fifteen were string variables with the names of the airports, the airport manager, phone numbers and street addresses, ownership status, various airport codes, and detailed research notes on each airport and the airport websites. There were eleven clusters of numerical variables, as follows. The "I.V." cluster housed the four independent variables, all dummies, describing the degree of *operational control* at each airport (low, medium, high, and a combined medium+high). This cluster also included a fifth variable which was the same information, but encoded as a string variable denoting each condition. The I.V. cluster was distinct and separate from the "Rubric" cluster. The Rubric cluster contained the branching paths of the ten conditions used to code the independent variables, as described above and illustrated in Figure 2. Additionally, ten variables described airport services (the "Services" cluster), eleven used satellite data and FAA data to describe the geography of the airport (the "Geography" cluster), there were six variables based on demographic data (the "Census" cluster), nine variables described the airplanes based at each airport (the "Base" cluster), seven variables tabulated the annual airport operations (the "Operations" cluster), eighteen variables encoded the degree of airport management activity and involvement (the "Governance" cluster), three variables measured the number and capabilities of competing airports (the "Competition" cluster), and three variables house the economic impact data (the "Dependent" cluster), for a total of 96 variables. The remaining variables are variations of that same data either standardized or transformed into natural logs.

Two concerns dominated the early stages of the data analysis. First, even the most casual review of the data showed an enormous variance in the dependent variables and the control variables across all three states and airports. For this study to be actionable, the development of a modest number of explainable, impactful, and efficient control variables was essential. Some sort of data reduction clearly was essential. Ideally, one variable from each cluster could "represent" that cluster in the analyses as it would be neither good research nor good management to attempt to model the dependent variables with fifty or more control variables. Therefore, one goal of the preliminary stages of the research was to determine, to any extent possible, which of the proposed control variables carried the most explanatory power, and which were not relevant or were duplicative. This was accomplished in three steps: by examining the descriptive statistics, deploying graphical analysis, and then producing a full correlation matrix.

Descriptive Statistics

First, a full set of descriptive statistics and frequency counts for the numerical data was developed (ignoring the data fields containing administrative items such as addresses and names). This analysis included means, medians, standard deviations, and measures of skewness and kurtosis and was presented in Tables 5a and 5b, above (for brevity, these tables present only those principal variables most relevant to the analysis, for reasons explained below). Many of the variables were severely skewed: eight of the dummy control variables were positively skewed and two were negatively skewed, while twenty of the ratio-scaled variables were positively skewed, with none negatively skewed. Second, the range of absolute values of the variables were very large, ranging from single digits (the number of runways at a focal airport) to billions (total income within the catchment area). Additionally, there were a total of 318 missing values which limited the usefulness of some variables in the analysis, mostly in the Base and Ops clusters.

Table 5a:

Descriptive Statistics of Selected Ratio-Scale Variables

(All airports, all states)

Cluster	Variable Name and Units of Measure	n	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Services								
	Serv - Airport Age (Years)	208	12.00	92.00	66.77	17.70	(1.04)	0.28
	Serv - Number of Runways	235	1	6	1.55	0.84	2.05	6.02
	Serv - Longest Runway (Ft.)	235	2,004	12,503	5,208.24	1,863.83	1.09	1.97
Geography								
	Geo - Airport Elevation (Ft.)	235	3	3,793	379.59	636.11	2.74	8.20
	Geo - Distance to CBD (Miles)	235	-	28	3.92	3.20	2.94	15.02
	Geo - Distance to Iconic Dest (Miles)	235	0.20	300.00	69.66	44.75	1.59	5.34
	Geo - Airport Size (Acres)	235	5	6,500	661.21	887.26	3.40	15.55
	Geo - Impervious Surfaces (Sq. Mi.) (15 mi.)	235	1.12	424.49	110.93	86.36	1.41	1.65
	Geo - Aqueous Surfaces (Sq. Mi.) (15-mile)	235	0.35	694.68	109.34	156.22	1.70	2.45
	Geo - Total Possible Land Area (Sq. Mi.) (15 mi.)	235	12.16	706.48	597.50	156.22	(1.70)	2.45
	Geo - % Land Area Developed (15 mi.)	235	1.10%	83.39%	0.20	0.18	1.72	2.61
	Geo - Land Remaining for Develop (Sq. Mi.) (15 mi.	235	5.50	673.52	486.57	178.16	(0.97)	(0.19)
Census Data								
	Cen - Population (15 mi.)	235	1,046	2,723,366	261,270	390,788	3.23	13.42
	Cen - Total Income ($) (15 mi.)	235	18,418,234	83,788,153,124	8,699,715,685	13,408,598,384	2.83	9.30
	Cen - Income Per Capita ($) (15 mi.)	235	14,586	58,746	29,984	6,737	0.61	0.92
	Cen - Total Employment (15 mi.)	235	386	1,363,819	123,736	195,148	3.27	13.63
	Cen - Civilian Emp. (15 mi.)	235	381	1,362,024	122,048	193,707	3.32	14.05
	Cen - $ Economic Intensity Per Sq Mi Imperv Surfac	235	3,797,460	203,631,564	53,674,038	40,509,364	1.51	2.26
	Cen - Employment Rate % (15 mi.)	235	28.00%	59.00%	43.88%	5.52%	(0.47)	(0.08)
Based Aircraft								
	Base - Single-Engine AC	233	-	358	56.78	60.15	1.93	4.50
	Base - Multi-Engine AC	219	-	109	9.95	14.94	3.19	14.08
	Base - Jet AC	203	-	174	7.12	18.28	5.37	38.29
	Base - Miltary AC	184	-	72	1.37	8.09	7.43	59.15
	Base - Total Aircraft	178	-	527	75.21	84.53	2.35	6.93
	Base - Jet AC as % of Total	174	-	55.00%	0.04	0.08	3.51	15.56
Operations at Each Airport								
	Ops -Total	235	200	364,071	44,899.81	50,210.89	2.56	10.28
	Ops - %_comm	235	0.00%	100.00%	2.18%	9.36%	6.92	59.18
	Ops - Air Taxi	164	-	131,154	3,511	11,327	9.35	101.22
	Ops - GA Transient	234	32	116,394	17,458	19,840	1.91	4.06
	Ops - Airlines	235	-	33,056	1,283	4,613	4.41	21.07
Governance								
	Gov - Index of Engaged Mngt	235	-	12	3.08	2.80	0.87	(0.13)
Competitive Airports								
	Comp - Number Airports (15 mi.)	235	-	5	0.96	1.14	1.20	1.18
	Comp - Number Runways (15 mi.)	235	-	10	1.58	2.11	1.59	2.48
	Comp - Total Runway Length (15 mi.)	235	-	74,579	9,448.73	13,812.46	1.86	3.63
Dependent Variables								
	DV Total Jobs	235	-	21,450	1,604	3,660	3.46	12.87
	DV Total Payroll ($)	235	11,000	3,043,040,000	86,579,957	252,063,258	7.76	82.22
	DV Total Economic Impact ($)	235	35,000	9,305,950,000	282,498,396	795,916,137	7.16	71.87

Notes: This table documents selected ratio-scale variables used as controls in this analysis, clustered into the major categories of airport data. The N is the count of airports reporting that condition. Not all airports report complete data to the FAA. The variable name has been edited for clarity. Note that many of these measures have a lower-boundary of zero which skews the data from a normal distribution, generally regarded as skewness between -2 to +2 and kurtosis between -7 to +7 (Hair et al. (2010) and Bryne (2010)).

Table 5b:

Frequencies of Principal Categorical Variables

(All airports, all states)

Cluster	Variable	Positively Reporting The Condition	Mean	Skewness	Kurtosis
State					
	Florida	104	0.440	0.233	-1.963
	North Carolina	69	0.290	0.912	-1.178
	Virginia	62	0.260	1.079	-0.844
I.V.: Degree of Operational Control					
	IV_D_ Low OperCntl	128	0.540	-0.181	-1.984
	IV_D_ Med OperCntl	17	0.070	3.323	9.120
	IV_D_ High OperCntl	90	0.380	0.485	-1.780
I.V. Coding Rubric					
	C1_ D_Airline Ops >99 Per Year	31	0.130	2.189	2.818
	C2_D_ Industrial Park On-site	20	0.090	2.993	7.017
	C3_ D_Mil-Ops >5340/Year	20	0.090	2.993	7.017
	C4_D_ De-Facto Privatized Airport	33	0.140	2.083	2.360
	C5 D_There is An Airport Authority	91	0.390	0.466	-1.798
	C5a_D_Management Involvement via Website	80	0.340	0.678	-1.554
	C5b_D_Mult Airports Managed	25	0.110	2.570	4.643
	C5c_D_Locally Operated	212	0.900	-2.724	5.467
	C6_D_Split Ownership	22	0.090	2.808	5.936
	C7_D_Airport Staff Uses Non-GOV Email	46	0.200	1.544	0.386
Services					
	Serv - D - Airport on NPIAS List	200	0.850	-1.985	1.956
	Serv - D_Paved Runway	224	0.950	-4.319	16.793
	Serv - D_Turf Runways	11	0.050	4.319	16.793
	Serv - D_ATC _Tower	60	0.260	1.130	-0.731
	Serv - D_US Customs	24	0.100	2.645	5.037
	Serv - D_FBO Outsourced	94	0.400	0.411	-1.847
Geography					
	Geo - D - Airport Access Constrained	26	0.110	2.498	4.279

Notes: This table documents the major binary (dummy) variables used as controls in this analysis. In each instance, a code of "1" is the positive condition for that variable. The n is the count of airports positively reporting that condition (coded "1").

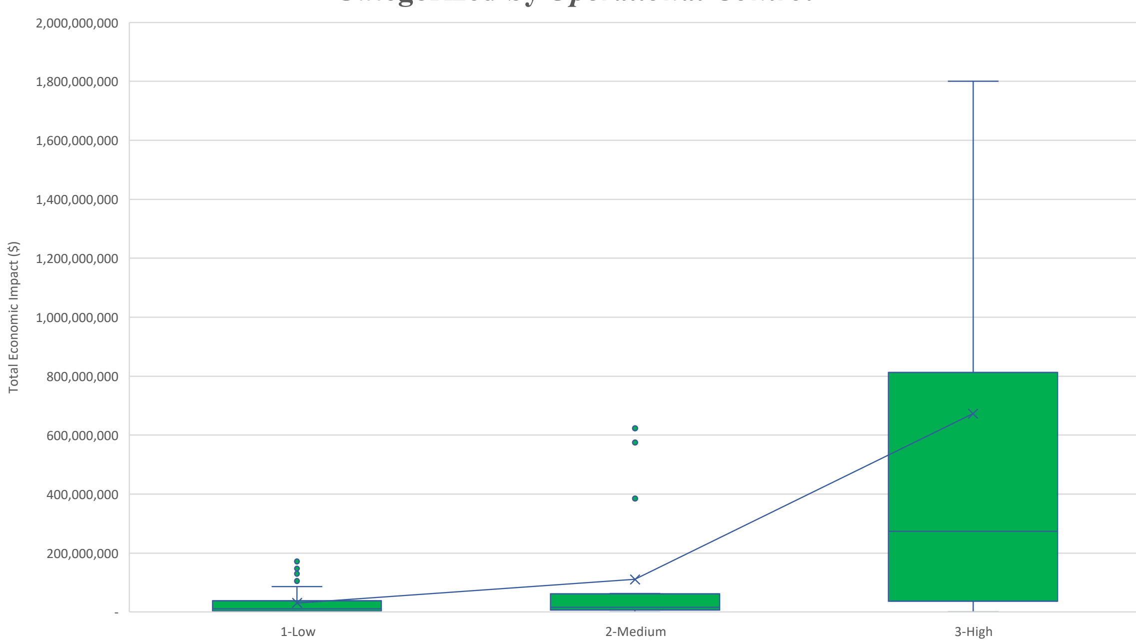
Graphical Analysis

The second step was to graphically examine the data using box plots, scattergrams and histograms. All the ratio-scale variables were paired with the independent variables and the charts examined for general trends, outliers, leverage points or other patterns. “Binning” the airports using different variables was informative and helped visualize the data. For example, there was a clear and positive relationship between the hypothesized independent variable, *operational control*, and the dependent variable at the “low” level but the relationship faded at the higher levels. A box plot of one of the dependent variables categorized by the independent variable is shown as Figure 4.

Several issues were identified with the box plots. First, many of the variables are bounded at zero or one (for example, the minimum number of runways is one, and many of the different types of base aircraft were reported as zero) which, as mentioned above, induces

Figure 4:

Box Plot of *Total Economic Impact* Categorized by *Operational Control*



positive skew to the data. Those lower boundaries made it difficult to distinguish between the different degrees of *operational control* using box plots.

Despite these issues, graphical analyses were informative. Several possible outlier airports were observed. The most prominent was the Piedmont Triad International Airport in Greensboro, NC (GSO). This airport has an economic impact of $9 billion, almost four times larger than any other airport in the study. This number was validated with the team at ITRE which produced the economic impact report, and they cited a number of aircraft factories and repair facilities at GSO which are unique. For example, Honda Corp. makes a very successful twin-engine executive jet at GSO and Boom Aerospace is using the same airport for the design and construction of the next-generation supersonic airliner. It was decided that while the economic impact results from GSO were accurate and justified, they were the product of truly rare conditions and unlikely to be reproducible by managers at other airports. Hence, GSO was removed from this study leaving an n=240 airports.

In a related investigation, the airport with the second highest level of economic impact was Cecil Airport outside of Jacksonville (VQQ) which is a civilianized military airport. It has extremely long runways, a heavy emphasis on air freight, a large industrial park on-site, and a management team which markets the airport as "the world's first horizontal-launching spaceport." Because Cecil's economic impact was well-justified but 60% less extreme than GSO, and because its impact was predicated upon activities which reasonably could be duplicated at other airports, it was retained in the study.

The box plots also highlighted other outliers. A small group of airports were found to have very unusual claims of economic impact (both unusually high and unusually low) without the traditional foundations of industries, based aircraft, airline service or other predictors of aeronautical success. After lengthy examinations of those airport web sites and discussions with the Economic Impact experts in Florida and North Carolina about the data collection and statistical processes used in their studies, it was decided for the purposes of this study to consider those five airports as outliers due to unjustified or improbable claims of economic impact or other observable oddities. These were: Clewiston Airglades airport (2I5), River Ranch Resort (2RR), Brooksville (X05), Virginia Tech (BCB), and Oak Island, NC (SUT). Airglades is in South Florida and is attempting to become an air freight hub for perishable air cargo. The River Ranch Resort airport is a private field at the south end of the Kissimmee Lakes wildlife reserve, about 90 miles due south of Orlando. It exclusively serves the Westgate Resort in River Ranch and has no general aviation services. Virginia Tech Airport serves a prestigious university, but the digital and statistical evidence suggested that airport's submission for the Virginia economic impact study was incomplete. Another outlier was Oak Island, NC. This facility claimed $278 million in economic impact which would be a strong result for any airport without commercial airline service. While the airport is close to popular beach resorts, the airfield is relatively small, has limited services, and there is no industry or aeronautical businesses on the field. Additionally, and most critically, it is run by a local celebrity who is featured on their airport's web site and for whom the airport has been renamed. Lastly, Brooksville, FL (X05) is a privately-owned airport serving a housing development. While the airport has no web site, no commercial service, no industrial parks nor any other economic drivers typical for airports, it claims an economic impact of $780 million which would put it in the top-ten of all general aviation airports in this study and twice the economic impact of the Gainesville airport. Lacking any substantive evidence to justify the claims of economic impact, these results for both Oak Island and Brooksville were considered public relations puffery. As a result of this analysis, and lacking any further evidence to explain these discrepancies, these five airports were considered outliers and removed from subsequent analyses, reducing the final number of airports in the study to n=235.

As a final *post hoc* validation of the outlier analysis, once the final models were created and tested, Cook's D distances were calculated for all of the remaining airports in the study. A general rule-of-thumb for classifying outliers with Cook's D is to exclude cases with values greater than 4/n, which is (in this study) a value of 0.01702 (Cohen, 1988). A scan of the data found only ten airports with Cook's D scores higher than that benchmark. A review of those ten found no significant discrepancies or questionable data. Hence, it seems plausible that the outlier analysis was reasonable and the retention of the 235 airports in the study was a reasonable and prudent decision.

Correlations and ANOVA

The third phase of analysis was to examine the correlation matrices between all the variables within a cluster, as well as to produce one large, unified matrix for the entire data set. Pearson correlations were used for the ratio-scale data and Spearman correlations were used for the categorical variables. As presented in Table 6, within each variable-grouping, statistically significant correlations with high absolute values were commonplace. For example, within the Census cluster, Cen_Employment_15 was highly correlated with both Cen_Pop_15 (.998, $p > .001$) and Cen_Income_15 (.986, $p > .001$). This suggested that many of the variables within each category were duplicative and multicollinearity might be a concern.

Correlations also were used to judge the face validity of the aggregated data and to search for potentially misleading data caused by an undetected data definition flaw or data collection flaw. This analysis led to the creation of several new categorical (dummy) variables. For example, the correlation of *Serv_Num_Runways* (at a focal airport) to *DV_Total_Eco_Impact* was .472 and significant, which seemed reasonable. The correlation of turf runways (*Serv_D_Turf)* to *DV_Total_Eco_Impact* was -.344 and significant, the direction of the correlation is as would be expected, and the magnitude seemed plausible as only the smallest airports use turf runways, and their economic impact is very limited. However, it was noted that Florida was the only state in this study to include airports with turf runways in their economic impact analysis. Airports with only turf runways were categorized with a new dummy variable to capture this effect in subsequent analyses.

As the correlational data was processed, a series of ad-hoc ANOVA analyses were attempted to better understand and interpret the data. For example, *Cat_Ownership* (a coding for privately/public-ownership) did not reflect a relationship with *DV_Total_Eco_Impact* whereas an ANOVA characterizing *State* to *DV_Total_Eco_Impact* was significant at .001. This could be a reflection of different techniques used by each state when developing their economic impact models or it could be a reflection of different levels of aeronautical activity in each state, but in either case it argues for the inclusion of State as a control variable in the final model.

Finally, the first important finding of this study developed from the correlational analysis. It was observed that the correlations among the full set of variables were highest for the 15-mile catchment area, lower for the 30-mile catchment and lowest overall for the 50-mile catchment. This pattern was true for almost every variable and analysis and can be observed in the first three columns of Table 6. In every instance, the correlations in the 15-mile catchment areas were higher than the 30-mile catchment area, and the 50-mile catchment area correlations were lower still. In most instances, the 15-mile catchment area correlation was significant at the 0.01 level, while the 30-mile zone only was significant at the 0.05 level and most of the 50-mile catchment correlations were not significant at all. This phenomenon was consistently observed for the census data, the geographic data, the competitive data, and the operational data. This evidence suggests that small airports serve highly localized markets and communities. Unlike major “hub” airports which have catchment areas measured in hundreds of miles, community airports have limited market areas, probably because pilots and passengers are unwilling to drive more than ten or fifteen miles to their community airport. The reduction in correlation coefficients suggests that excessively large catchment areas diluted the economic impact of any given airport, dissipating that airport’s economic contribution to the community in the general economic “noise” of the region. As a result of this finding, subsequent analyses were limited to the 15-mile catchment area variables.

The correlation analysis suggested one other preliminary finding, which was that the three dependent variables are highly correlated with each other. They seem to be duplicative reflections of the same underlying measure of economic activity. diluted the economic impact of any given airport, dissipating that airport’s economic contribution to the community in the general economic “noise” of the region. As a result of this finding, subsequent analyses were limited to the 15-mile catchment area variables.

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Table 6:

Correlations (Pearson R) of the Dependent Variables and Selected Catchment Area Variables

	DV Total Eco Impact	DV Total Pay	DV Total Jobs	Cen Pop 15	Cen Pop 30	Cen Pop 50	Cen Income 15	Cen Income 30	Cen Income 50	Cen Employ 15	Cen Employ 30	Cen Employ 50	Geo Imperv 15	Geo Imperv 30	Geo Imperv 50
DV Total Eco Impact	--														
DV Total Pay	.973**	--													
	<.001														
DV Total Jobs	.946**	.972**	--												
	<.001	<.001													
Cen Pop 15	.353**	.391**	.381**	--											
	<.001	<.001	<.001												
Cen Pop 30	.258**	.289**	.272**	.902**	--										
	<.001	<.001	<.001	<.001											
Cen Pop 50	.131*	.153*	.134*	.661**	.856**	--									
	0.045	0.019	0.04	<.001	<.001										
Cen Income 15	.361**	.400**	.391**	.986**	.912**	.680**	--								
	<.001	<.001	<.001	<.001	<.001	<.001									
Cen Income 30	.237**	.267**	.247**	.836**	.967**	.850**	.878**	--							
	<.001	<.001	<.001	<.001	<.001	<.001	<.001								
Cen Income 50	0.101	0.123	0.104	.581**	.790**	.961**	.625**	.842**	--						
	0.124	0.059	0.112	<.001	<.001	<.001	<.001	<.001							
Cen Employ 15	.352**	.390**	.380**	.998**	.899**	.654**	.987**	.839**	.581**	--					
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001						
Cen Employ 30	.254**	.285**	.267**	.896**	.997**	.852**	.910**	.977**	.800**	.897**	--				
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001					
Cen Employ 50	0.122	.144*	0.124	.648**	.845**	.995**	.672**	.855**	.978**	.644**	.848**	--			
	0.061	0.027	0.057	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001				
Geo Imperv 15	.390**	.420**	.416**	.903**	.855**	.673**	.898**	.797**	.584**	.894**	.840**	.647**	--		
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001			
Geo Imperv 30	.229**	.249**	.239**	.705**	.872**	.813**	.712**	.833**	.729**	.697**	.858**	.787**	.848**	--	
	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		
Geo Imperv 50	0.055	0.063	0.054	.373**	.608**	.828**	.376**	.587**	.757**	.364**	.595**	.806**	.548**	.829**	--
	0.397	0.333	0.411	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	

** Correlation is significant at the 0.05 level (2-tailed).*

*** Correlation is significant at the 0.01 level (2-tailed).*

Indices and Interaction Effects

A series of additional control variables, both categorical- and ratio-scaled, were created to reduce the number of variables needed in the OLS regressions and to improve the accuracy of the measurement of direct interaction effects. (Readers will recall that a number of “coding” variables also were developed for the coding rubric of the independent variable. These variables were not used in the main analysis, but they were retained in the database to allow the validation and confirmation of the coding rubric by other researchers.) While many indices were tested, the following items were retained in the final dataset, along with the numerical scale used, the units of measurement, and the cluster to which it was assigned:[18]

Above Average Airline Operations per Year. Categorical scale (dummy). The Rubric cluster. This variable was coded from the FAA 5010 report. Overall, an airport is coded “1” is the airport had more than 1,283.5 airline operations/year and “0” if they had fewer. Only 26 airports had “above average” airline operations (and only 16 others had any airline service at all). The average was calculated using all 235 non-outlier airports. Ideally, a better discriminant would be to use the median value for the airline operations but in this case the median is zero due to the large number of airports (193) reporting no commercial traffic. The degree of variance in the data is quite large: the standard deviation is four times larger than the mean at 4,613.3, and the entire variable is heavily positively skewed. While a reader will not be surprised at the large number of airports lacking commercial service (after all, only 493 of the 20,0002 airports in the FAA database have any airline activity) one might be surprised at the variance in airline data. For example, some airports have service that only is available a

[18] Readers are reminded that the catchment area retained in the study was a circle 15-miles in radius. A 15-mile radius encompasses 706.84 sq. mi.

few times each week, not the normal daily service. Start-up low-cost airlines frequently fail, leaving the airport with less airline service than anticipated. Airlines also are quick to cull non-performing routes so an airport may lose their service mid-way through the year due to lack of patronage. Lastly, some airlines serve some resort destinations purely on a seasonal basis. The ratio-scale version of this variable was retained in the Operations Cluster. Variable Name: *Rubric_C1_D_Airline_OpsGT1284.*

Above Average Military Operations per Year. Categorical scale (dummy). Rubric cluster. While 193 airports reported some degree of military traffic only 20 airports reported the "above average" condition which could be anticipated to bolster economic impact. The coding assigned the value of "1" if the airport supported 5,340 or more military operations/year and "0" if they had fewer. As with the airline traffic, this was computed using all of the 235 study airports. The range is from zero operations to 53,899 operations per year which produces a standard deviation approximately twice the mean. Once again, while the median would have been a better metric the mean was used because 80.4% of all the operations came from just 33 airports and the median would have been zero. Just a dozen airports delivered 50.4% of the 448,988 reported operations: Elizabeth City, Maxton, Bonifay, Pensacola, Jacksonville, Newport News, Kinston, Tallahassee, Wilmington, Albemarle, St. Petersburg-Clearwater, and Jacksonville. This variable was coded from the FAA 5010 report, and the ratio-scale version of the variable also was retained in the Operations cluster. Variable Name: *Rubric_C3_D_MilOpsgt5340.*

Weak Airport Authorities. Categorical scale (dummy). Governance cluster. During the collection and coding of the "Governance" variables, a pattern was observed suggesting that not all airport authorities were equally vibrant and involved. Some seem to be highly energized and motivated while others are less engaged. The *operational control* coding rubric required that any airport which the FAA indicated was supervised by an authority was automatically categorized as "high" *operational control* (Question C5). However, it became apparent that some of those "high" airports actually scored "low" on digital governance behaviors. In other words, those airports had the designation of "high" *operational control* but demonstrated the behaviors expected from the "low" *operational control* condition. This was a challenge to the core hypotheses upon which this study was based, so a dummy variable was created to capture this variance. Specifically, the coding assigned a value of "1" if the authority was "weak" which was defined as having fewer than four governance behaviors demonstrated on their web site, and a value of "0" (not weak) if they had four or more governance behaviors. Across the three states, 30 airports had airport authorities which showed little-to-no evidence of being active, engaged or involved. While the sample is small, the phenomenon appears to be confirmed by the descriptive statistics. Table 7 shows that airports with weak airport authorities average 33.6% fewer operations annually than peer airports with more active airport authorities. Airports with weak authorities generate only 4.51% of the Total Economic Impact of their more active brethren. In fact, airports without an airport authority out-perform airports managed by weak airport authorities, suggesting that unless the airport authority is actively engaged it's better to not have any airport authority at all. Variable name: *Gov_D_AA_Weak.*

Incorrect FAA Data. Categorical scale (dummy). Governance cluster. In an observation related to the situation described above, a dummy variable was created to model the effect of incorrect FAA data on the Form 5010 report. This was noticed during the "digital governance" review of the airport web sites. Prior to this discovery, it had been assumed the

FAA data was accurate. However, a small number of airport websites showed instances in which there were operational airport authorities which the FAA data did not report. For coding purposes, this variable was assigned a value of "1" if the FAA data did not indicate an airport authority was operating at the airport, and a value of "0" if the FAA data correctly recorded the airport management situation. A total of 19 airports were identified under this condition. Two of those airports had "weak" authorities. The impact of this condition upon the dependent variables is unclear and no hypotheses are suggested, but on the possibility that

Table 7:

Comparison of "Strong" Versus "Weak" Airport Authorities

State	Airport Authority?	# Airports	Average, Total Annual Aircraft Operations	Average, Total Eco_impact
FL		104	68,729	$354,716,683
	No Airport Authority	76	63,326	$304,868,684
	Yes, There Is an Airport Authority…	28	83,395	$490,018,393
	...It's a Strong Authority	26	88,085	$525,875,231
	...It's a Weak Authority	2	22,422	$23,879,500
NC		69	27,018	$335,162,029
	No Airport Authority	36	21,632	$81,241,944
	Yes, There Is an Airport Authority…	33	32,893	$612,165,758
	...It's a Strong Authority	20	43,151	$987,497,500
	...It's a Weak Authority	13	17,112	$34,732,308
VA		62	24,829	$102,748,516
	No Airport Authority	32	22,322	$17,945,281
	Yes, There Is an Airport Authority…	30	27,504	$193,205,300
	...It's a Strong Authority	15	37,776	$360,305,333
	...It's a Weak Authority	15	17,232	$26,105,267
Grand Total, All States		235	44,900	$282,498,396

this could be a condition of significance the variable was created and retained in the dataset. Variable name: *Gov_FAA_Data_Wrong.*

Total Land Area of the Catchment Zone. Ratio scale. Square miles. Geography cluster. This value was hypothesized to be an approximate measure of total development potential surrounding an airport. It was computed by subtracting the square miles of aqueous surfaces from the total square miles of a 15-mile catchment area; which is to say, if it is not water it must be land. Variable name: *Geo_Total_Land_Area.*

Proportion of Land Area Developed. Ratio scale. Percent. Geography cluster. Computed to merge two variables into one by dividing, for each airport, the square miles of impervious surfaces by the total land area of the catchment zone computed by the previous variable. This is a measure of undeveloped potential. For example, the two general aviation airports around Tampa and St. Petersburg, St. Pete-Clearwater International, and Albert Whitted Airport, have less than 20% of their land area available for future development. This suggests their potential for future growth might be limited or, at least, come at a very high redevelopment cost. In contrast, the three least-developed catchment areas (Montgomery County, NC; Franklin Regional, VA; and Mountain Empire, VA) were 95% undeveloped. This pattern suggests that, all other things being equal, these airports could easily and inexpensively leverage higher than normal economic impact by attracting industry for development. Variable name: *Geo_PC_Dvlpd.*

Undeveloped Land Area. Ratio scale. Square Miles. Geography cluster. This variable is another measure of the latent potential of a catchment area. Computed to merge two variables in to one, by subtracting from Total Land Area the Impervious Surfaces. A measure of latent potential. Variable name: *Geo_Rmng_Land.*

Total Airport Services. Ratio scale. Summation. Services cluster. This was an effort to enhance the parsimony of the analysis by merging six variables into one. The variable is a simple summation of the relevant variables in the Services cluster, from the Form 5010 report (*Serv_D_NPIAS + Serv_Num_Runways + ZServ_LongestRnwy + Serv_D_ATC_Tower + Serv_D_Customs+ Serv_D_ContractFBO).* Note that *Serv_LongestRnwy* has been recoded into standardized form (prefaced with a "Z"), so it is a ratio-scale variable and can induce a negative value for airports with short runways. Variable name: *Serv_Total_Services*.

Local Employment Rate. Ratio. Percent. Census cluster. Computed to merge two variables by dividing Civilian Employment by Total Population. Variable name: *Cen_EmployRate_15.*

Economic Intensity. Ratio. Dollars/Sq.Mi. Census and Geography cluster. Designed to merge two variables into one and distinguish "lively" economic areas from less economically successful ones. Computed by dividing total household income within the catchment area by the square miles of impervious surfaces. Variable name: *Cen_Eco_Intensity_15.*

Island Airports. Ordinal scale (dummy). Geography cluster. This variable was created to capture the economic impact of relative isolation. These airports were classified as having "impaired access" to adjacent communities when ground transportation was considered. The observation inherent in this variable is that a normally situated airport might attract customers from any direction, but if a direction is blocked by a large body of water the ability of that airport to generate substantial economic impacts would be degraded. A major portion of the variance in the data should be captured by Geo_Aqueous15. While originally envisioned as merely a technique to identify island airports, as the coding was developed it was noted that some mainland airports were equally isolated and hard to reach. The final coding rule was any airport was coded “1” if the airport was (a) on an island, a peninsula, or within one mile of the shoreline and (b) served by only one road, such as Cedar Key, FL. All other airports, including airports on swamps, farmlands, mountains, or even desolate areas are coded “0.” Two examples of these airports are included in Appendix 5. Variable Name: *Geo_LimitedAccess.*

In addition to the variables described above, other variables were considered and discarded. For example, Florida is the “Sunshine State.” Could the weather make a difference in the local airports? Do larger states have greater economic impact simply because they have more airports? Could age distribution in the population make a difference? None of those concepts proved helpful — on average, North Carolina enjoys 9% more sunny days than Florida — and were discarded.

Factor Analysis

A series of factor analyses were performed to systematically reduce the number of control variables in the data set. The factor analyses used principal axis extraction with direct oblimin rotation and the factor scores were saved in the data set. Both the KMO test and Bartlett’s test for sphericity were computed.

The factor analysis was made more complex due to “not positive definite” (NPD) conditions occurring during some of the analyses which causes the statistical procedure to stop without extracting factors. NPD conditions result under three conditions: (a) if the eigenvalues of the correlation matrix have a negative sign, (b) if there are linear dependencies among the variables (e.g., variable 3 is the sum of variables 1 and 2), or (c) if there are more variables than cases, when listwise deletion eliminates many cases (Wothke, 1993). The last two conditions were present in the airport dataset. For example, many of the based-aircraft observations from individual airports were categorized as missing, which caused the process to delete dozens of airports from the computation. A related problem stemmed from the variable *Base_TotalAC* was the sum of all the airplanes in the other categories. The NPD situation limited the choices and combinations when attempting to build factors. A number of variables cross-loaded on to several factors. In an iterative process, the variables with the highest cross-loadings were excluded and the analyses recomputed.

The process produced eight factors with reasonable loadings and reduced (but not eliminated) cross-loadings. The factors were characterized as primarily dealing with the following traits: (1) Services, (2) Facilities, (3) Geography, (4) Water, (5) Operations, (6) Census, (7) Bigger Planes, and (8) Competition.

However, this result was not particularly satisfactory because there were contradictory loadings between the factors. Many variables appeared in multiple factors. The signs of the factor loadings were occasionally contradictory to theory. The cumulative explanatory power of the factors varied from 27% to 74%. Several times more than 25 iterations were required to extract the factors which suggest lack of clarity in the analysis. These observations suggested at least some of the factors did not succinctly capture the variance in the data and it is likely the NPD issue degraded the overall quality of the factor results. When the eight new factor variables were used as controls in a regression model (presented in the next chapter, below), the factors did not attain statistical significance and the goodness-of-fit was relatively low.

Another use of the factors, however, was to evaluate each variable's factor loadings as identifiers for one or more of the variables from each cluster which had the greatest explanatory power compared to their peer variables. Two decision-rules were used. First, the variable could be selected if the absolute value of its factor loading was the highest of all the variables in that factor. For example, five variables contributed to Factor 3, Facilities, but *Geo_Imperv_Surfaces_15* was the variable with the single highest factor loading, at .608. Secondly, a variable could be selected if it appeared in only that one factor, which is to say its covariance with the other variables was unique. For example, two variables participated in Factor 4, Water. *Geo_Elevation* had the highest loading, at .573, so it was selected. However, *Geo_Aqueous15* did not appear in any other factors, so it was also selected for its ability to bring a unique degree of explanatory power. This example is probative in that it demonstrates the manner in which the two variables work in opposition, which is to say large values of aqueous surface areas are inversely proportional to higher elevations ($r = -.362$), $p < .001$).

This variable selection process worked efficiently and suggested nine specific variables which could be included directly in the preliminary analyses. These variables are presented in Table 8 and these became the initial control variables in the base regression models. However, even this outcome was problematic. Many of the selected variables were highly correlated which has the potential to produce multicollinearity in the regression models.

Table 8:

Preliminary Selection of Control Variables Based on Factor Loadings

Factor	Factor Name	Highest Loading Variable (H) or Highest Unique Variable (U) from Each Factor	Loading	Cluster
1	FAC1_Services	Dummy_ATC _Tower (U)	0.833	Services
		Longest Runway (Ft.) (H)	0.744	Services
2	FAC2_Facilities	Airport Age (Years) (H)	0.455	Services
3	FAC3_Distances	Impervious Surfaces, 15-Mi. (H)	0.608	Geography
4	FAC4_Water	Aqueous Surfaces, 15-Mi. (U)	-0.478	Geography
		Airport Elevation (Ft.) (H)	0.573	Geography
5	FAC5 Operations	Log, Total Income, 15-Mi. (H)	0.906	Census
6	FAC6 Census	Log, Total Employ, 15-Mi. (H)	-0.453	Census
7	FAC7 Bigger Planes	Based Mutli-Engine AC (H)	-0.456	Based
8	FAC8 Competition	# Comp Runways, 15-Mile (H)	0.314	Competition

Multicollinearity reduces the stability of regression results and in so doing induces unexpected outcomes, such large variability in regression coefficients, fluctuations in statistical significance and coefficients with theoretically incorrect signs. In those instances, the problematic variables were removed, and other variables substituted. Two rules were used in the substitution process. First, the replacement variable had to come from the same variable cluster because the variables within each cluster are theoretically related to the same underlying variance controlling trait. Second, the selected replacement variable would be the one in the cluster with a correlation coefficient closest .500.[19] This rule reflects two conflicting conditions: (a) the need to select a variable which has a relationship with the other variables in the cluster but (b) not be so strongly correlated as it could re-introduce the multicollinearity problem.

Baseline Model of Control Variables

The initial efforts at model-building began by using the factor analysis variables and then the variables identified in the factor analysis. The dependent variable was the natural log of *DV_Total_Eco_Impact.* This initial model was tested on the principal airports of interest — those in Florida — and then validated on the overall data set. The results were generally unsatisfactory. The factor model (Model 1) was marginally significant but only one of the factors achieved significance. Both the Florida model (Model 2) and the validation model (Model 3) achieved significance: Florida airports: $R^2 = 0.780$, $F(9,93) = 27.359$, $p < .001$; validation model: $R^2 = 0.746$, $F(9,182) = 52.936$, $p < .001$). However, between Model 2 and Model 3 the coefficients were substantially different, several of the coefficients were

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[19] As part of the planning for the data analysis, correlation matrices were produced for each cluster of variables using only the airport data from North Carolina and Virginia. This avoids the problem of using data from Florida to predict itself.

extremely close to zero which makes them less than useful for management, several variables had the sign of the coefficient change, and there was a high degree of multicollinearity induced by the Census variables (greater than 100) as measured by the variable inflation factor. An effort was made to make the models more parsimonious, devoid of multicollinearity, more stability, and to bring the analysis into congruence with theory by reviewing the contribution of each cluster.

Table 9:

Initial Regressions of Control Models, Using Factor Analysis Guidance

(Dependent Variable: DV_Log_Total_Eco_Impact)

Regression Using the Factors	Model #1, FL Only Stan Beta	Sig	Variable	Model #2, FL Only Stan Beta	Sig	Model #3, All Cases Stan Beta	Sig
FAC1_Services	0.790	**	Dummy_ATC _Tower	0.099		0.137	*
			Longest Runway (Ft.)	0.560	**	0.529	**
FAC2_Facilities	-0.085		Airport Age (Years)	0.173	**	0.088	*
FAC3_Distances	-0.010		Impervious Surfaces, 15-Mi.	-0.082		-0.076	
FAC4_Water	0.024		Aqueous Surfaces, 15-Mi.	0.148		0.127	**
			Airport Elevation (Ft.)	0.079		-0.037	
FAC5 Operations	-0.008		Log, Total Income, 15-Mi.	-0.242		-0.674	
FAC6 Census	-0.080		Log, Total Employ, 15-Mi.	0.484		0.930	*
FAC7 Bigger Planes	-0.070		Based Mutli-Engine AC	0.226	**	0.198	**
FAC8 Competition	-0.072		# Comp Runways, 15-Mile	-0.042		-0.045	
F	17.08	**	*F*	27.359	**	52.936	**
R2	0.537		*R2*	0.780		0.746	
Adjusted *R2*	0.507		Adjusted *R2*	0.752		0.732	

The initial model included three variables from the Services cluster: *Serv_Longest_Rnwy, Serv_Airport_Age* and *Serv_D_ATC_Tower*. Using three variables from one cluster would not be a parsimonious design if it could be avoided. *Serv_Longest_Runway* was consistently significant and theoretically appealing so it was retained. The *Serv_Airport_Age* variable was statistically significant only occasionally and usually only with respect to Florida airports. It was deemed too unstable to include in the final model. The *Serv_ATC_Tower* variable suffered from multicollinearity with the Longest Runway so was replaced with the dummy variable for the airport being listed in the NPIAS system (*Serv_D_NPIAS*). This proved to be a broader and more impactful implementation perhaps due to the fact a medium-sized airport can be listed in the NPIAS roster while not having the expense of an air traffic control facility.

When testing the "Operations" cluster, neither the total operations at an airport nor the volume of airline traffic were included in any factors. This was a problem because decades of personal experience suggest that traffic in general and airlines in particular are enormous contributors to the economic success of an airport. It was further noted that only 41 of 235 airports had any airline service and only 26 had "above average" airline traffic, which degrades the influence of the variable. It is likely that much of the variance from *Ops_Airlines* is being captured by the *Serv_Longest_Runway* variable as they are highly correlated ($r = .500$, $p < .001$) and 100% of all the cases in this study reported on their runway length. Of all the "Operations" data, *Ops_GA_Visitors*[20] proved to be consistently significant for both the Florida model and the overall model, and the results were more stable, so it was included in the final iteration.

The initial model included two "Census" variables and they were the greatest source of multicollinearity. Additionally, the initial model included two satellite-derived "Geography" variables. In an effort to model the airports as parsimoniously as possible while still being consistent with the factor analysis, *Geo_Impervious_15* was combined with one of the Census variables, *Cen_Income_15*, into an index. This new variable, *Cen_Eco_Intensity_15*, reduced

[20] Just a reminder to readers that "GA" refers to "General Aviation" and is not an abbreviation for the state of Georgia.

two variables into one by dividing the total income reported in the catchment area (*Cen_Income_15*) by the square miles of impervious surfaces in the catchment area (*Geo_Impervious_15*). This index captured in one succinct descriptor the economic energy within the catchment area, the moderating effects of navigable waters and the differences between industrialized catchment areas as opposed to rural ones. *Cen_Eco_Intensity_15* proved to be a useful integration of both geographic and census information.

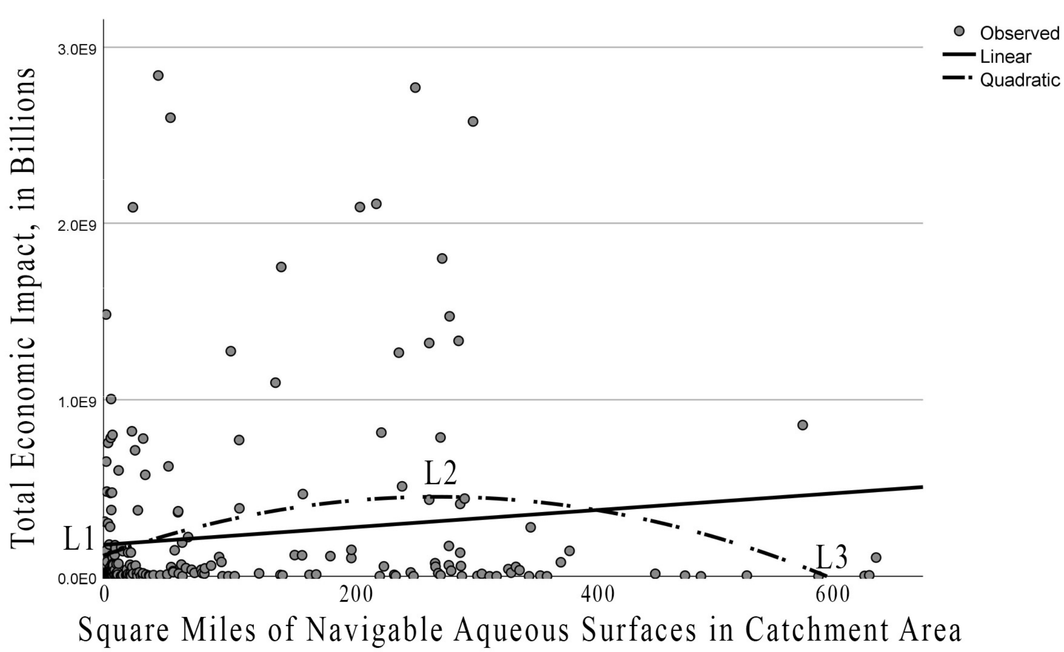
Consideration of Quadratic Effects

One particular interest of this study was the effect of navigable waters upon the economic impact of an airport. For example, the correlation of the square miles of aqueous surfaces (*Geo_Aqueous15*) to population (*Cen_Log_Pop15*) was negative and significant, which carries face validity in any given area: the more navigable water the less land there is for people to live and work. Consider a conceptual continuum of economic impact. At the lowest level, and with all other factors being equal, a landlocked airport can generate a certain level of economic activity, hypothetically called L1. This is the baseline for any airport. Moving up the continuum, a beachfront airport might benefit from a matching degree of local industry but also earn a secondary benefit from tourism, enhanced home values and recreational industry (boat sales, for example), all of which is unobtainable to the landlocked airport, and which creates a greater level of economic impact, termed L2. But at some point, too much water isolates the community and degrades an airport's ability to deliver economic benefits, producing an economic impact designated L3. Figure 6 shows the results of an exploratory regression analysis of this possibility which was performed without other control variables. The results were consistent with this suggestion. In a linear formulation, *Geo_Aqueous15* predicted *DV_Total_Eco_Impact*, $R^2 = .019$, $F(1, 234) = 4.560$, $p = .034$, but the quadratic version offered improved results, $R^2 = .066$, $F(1,234) = 8.431$, $p <.001$.

Studying the raw data, it became apparent that not all "navigable waters" would have identical effects. Only eight airports in the study had more than 500 square miles of aqueous surfaces (approximately 85% water). The island airport of Fernandina Beach, Florida, for example includes 342 square miles of buildable land within the catchment area while Key West, Florida encompasses just 78 square miles of land. To further explore this possibility, and as mentioned above, the new "isolation" variable was modeled to capture the effects of isolation upon airport economic activity, Geo_D_LimitedAccess. The airports on the Outer Banks of North Carolina, the airports on Tangier Island in Virginia, Marathon Island in

Figure 6:

Test of the Quadratic Relationship Between Aqueous Surfaces and Economic Impact



Florida, the peninsula-based airport at Cedar Key, Florida, and airports surrounding the

Everglades National Park may demonstrate this effect, as well as Zephyr Hills Airport (FL) which is adjacent to enormous wetlands. A regression adding *Geo_D_LimitedAccess* to the navigable waters was attempted and produced enhanced results, $R^2 = .134$, $F(2,231) = 17.797$, $p < .001$. Based on these tentative findings, it was decided to explore their impact in the full model.

Testing OLS Assumptions

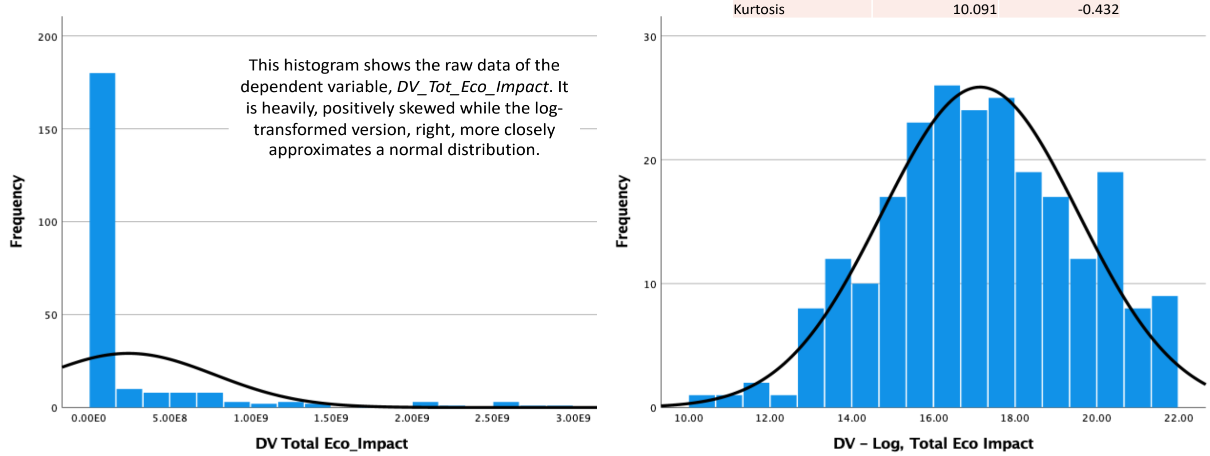
There are several crucial assumptions underpinning the OLS regression statistics which were used in this study and efforts were made to confirm the data was in compliance with those assumptions. First, OLS regressions assume the residuals will be normally distributed. This is important because it enhances the reliability of the predictions, it generates more accurate confidence intervals and is very helpful for hypothesis testing. However, it is a challenge to produce normally distributed residuals from data which itself is not normally distributed, which was the case in this study. Many of the variables in the Census, Based, and Service Clusters were not normally distributed and suffered from extreme skewness. After extensive consideration of the alternatives, it was found that a log-transformation of the problematic variables resolved the issues of normalcy. This transformation was performed reluctantly because it is difficult to explain and interpret log-transformed regression coefficients to the general public which is the audience for this research. Nonetheless, when the census and dependent variables were transformed the histograms of the residuals nicely fitted the normal distribution: *Geo_Aqueous_15, Cen_Pop_15, Cen_Income_15, Cen_IncPerCapita_15, Cen_Eco_Intensity_15, DV_Total_Jobs, DV_Total_Payroll* and *DV_Total_Eco_Impact*. Figure 7 shows an example of one such transformation.

Another requirement is for the regression model to be linear in both its error term and coefficients. Other than the possible influence of the variable *Geo_Aqueous_15*, there was no evidence or theory to believe these relationships were not linear. Another concern could be that there may be a correlation between the independent variables and the error term, which is a manifestation of endogeneity. This can be caused by measurement errors of the independent variables or biases caused by omitted variables. In this case, one could argue there almost

Figure 7:

The Effect of the Log Transformation

	DV Total Eco_Impact	DV - Log, Total Eco Impact
N	235	235
Minimum	35,000	10.46
Maximum	2,839,786,000	21.77
Mean	243,936,637	17.1439
Std. Deviation	534,092,087	2.40596
Skewness	3.148	-0.124
Kurtosis	10.091	-0.432



certainly are measurement errors in some of the data (especially in the FAA Form 5010 report, as discussed above). But it was felt that any important measurement errors would be rare, small, and relatively unimpactful because for the most important observations the quality of the data was high. For example, the data reported from busy airports with air traffic control towers would be far more reliable and impactful to this study than the traffic “guesstimated” at an airport with a turf runway managed by a distant clerk in a government office. The concern of omitted variables is always a worry but, in this case, with 131 variables from which to choose, one would be hard-pressed to find an influential trait that was not represented in the data in some form.

Another requirement is for the error term in a regression to be random and unpredictable. However, any correlation between the independent variables and the error term would imply the two terms are related in some way, which would make the error term a predictable value. This is termed endogeneity and can be caused by measurement errors or omitted variables. In this study, it was resolved by the efforts to use highly automated data sources (satellites, census, airport traffic data) and the deployment of a rich data set to minimize the chance of an omitted variable issue. Additionally, the error terms are supposed to be independent of other error terms; one estimated error prediction should be unrelated to the error terms adjacent to it. This is most often an issue with time-series models. This study minimizes this risk of heterogeneity by restricting the analyses to cross-sectional data (with the exception of two small supplemental analyses explained below).

Homoscedasticity of the error term is another concern; this implies the variance of the error term is constant over the breadth of the study. Usually this is modeled with scatterplots of the true values versus the residuals. If the error terms display a pattern (a “fanning” of the data, or a histogram showing a curve, for example) it might be indicative of a missing variable or evidence the relationship is not linear. If that occurred, the model has failed to meet the assumption of homoscedasticity. To this end, numerous scatterplots were produced and examined to ensure there was no obvious pattern in the residuals.

The last concern is one that occurs when the independent variables, either alone or in combination, have a perfect linear relationship with other variables. This is similar to both the NPD issue discussed in the factor analyses and the multicollinearity issue mentioned in the regression analyses. To that end, the correlation matrix was examined closely to avoid selecting variables which would be problematic. Nonetheless, early in the model-building phase it was necessary to remove some of the proposed control variables and substitute others from the same cluster, using the process described above.

CHAPTER 6: FINDINGS

The final models support the hypothesis that the degree of *operational control* has a significant and positive impact upon the economic performance of the organization. Three dependent variables were used in these analyses: the total economic impact (*DV_Total_Eco_Impact*), total payroll (*DV_Total_Payroll*) or total jobs (*DV_Total_Jobs*). All three variables were natural-log transformed prior to analysis. The final models are presented in the following four tables. Table 10 features three primary analyses for the airports in the Florida. Table 11 displays the same presentations for all three of the dependent variables, again, just using the Florida airports. Table 12 validates the Florida results by expanding the analysis to include the airports in all three states (n=235). Table 13 allows an easy comparison of the validation models for all three dependent variables.

The Baseline Model of Total Economic Impact

There are three regression results presented in Table 10. These are the results of modeling just one of the three dependent variables, *DV_Log_Total_Eco_Impact*. The first column shows the results when using only the controls (Model 4); this should be construed as the "baseline model." The second column is Model 5 builds on the baseline result by including the "medium" and "high" levels of the independent variable. The third column, Model 6, substitutes the "low" condition of *operational control* into the same model and is further discussed below.

Considering Table 10, it is useful to notice the stability of the coefficients; both the signs and the magnitude of the coefficients remain very similar across all three presentations. There are five impactful control variables: the length of the longest runway, being included on the NPIAS list of airports by the FAA, the number of based multi-engine aircraft, the number of visiting GA aircraft, and the economic intensity of the catchment area. When the independent variables are added, the coefficients shift very little. The F-tests are highly similar and the R^2 is strong and stable. These findings offer support for the hypothesis that the degree of *operational control* significantly contributes to the economic impact of the airport. Importantly, and unlike when the facto analysis was attempted, the variable inflation measure (VIF) statistic remains under two, which suggests the variable substitution process outlined above controlled the problems with multicollinearity.

Another alternative test of the general validity of the models was to consider the effect of "low" *operational control*. This concept is featured in the third column of Table 10, designated Model 6. The principle independent variable in this study was a dummy variable coded for "high" *operational control* (as shown in the tables, the "medium" degree of *operational control* also was included but never achieved significance). It seemed prudent to test the obverse hypothesis, which would be that airports with unengaged, lackadaisical airport management should be less economically successful than their peers operating under a condition of "high" *operational control*. This analysis was conducted using the same model with merely the substitution of *IV_D_Low_OperCon* in the place of the two other independent variables. This test found statistical significance in both instances, with minor fluctuations in the control coefficients; $R^2 = .815$, $F(8,85) = 46.889$, $p < .001$. Importantly, the control variables which were significant in Models 4 and 5 remained significant in this supplemental test and their coefficients remained generally unchanged.

Table 11 expands the analysis to view of all three log-transformed dependent variables (notice than Model 5, from Table 10, is duplicated in Table 11 to facilitate comparisons). As expected, there are slight differences in the standardized beta coefficients, but the results are

Table 10:

Primary Analysis
Dependent Variable: DV_Log_Total_Eco_Impact
Using All Controls and Measuring the Effect of IV
Florida Airports Only

Variable	**Model 4: Base Model with Controls Only** *Standardized Beta*		**Model 5: Full Model with I.V.** *Standardized Beta*		**Model 6: Full Model with Negative I.V.** *Standardized Beta*	
(Constant)						
Dummy_Florida	n/a		n/a		n/a	
Serv - Longest Runway (Ft.)	0.538	**	0.443	**	0.471	**
Serv - D - Airport in NPIAS List	0.206	**	0.202	**	0.200	**
Geo - Distance to CBD (Miles)	-0.080		-0.085	~	-0.085	
Base - Multi-Engine AC	0.165	**	0.137	**	0.149	*
Ops - GA Transient	0.198	**	0.171	**	0.157	*
Comp - Number Runways, 15-Mi.	-0.017		-0.013		-0.017	
Cen - Log, Eco_Intensity, 15-Mi.	0.196	**	0.225	**	0.218	**
IV_D_ Med OperCntl			0.029			
IV_D_ High OperCntl			0.171	**		
IV_D_ Low OperCntl					-0.143	*
F	F(7,86) = 50.422	**	F(9,84)=45.910	**	F(8,85) = 46.889	
R2	0.804		0.818		0.815	
Adjusted R2	0.788		0.799		0.798	
Average VIF for the Model	1.382		1.564		1.518	

** Indicates significance at 0.05.*   *** Indicates significance at 0.01*

generally very consistent, the same variables are significant in each case, the F-test is stable and the R^2 is robust.

Table 12 and 13 presents the validation models in which the sample size is expanded from just the Florida airports to include the airports of Virginia and North Carolina. To preserve consistency with Tables 10 and 11 and to facilitate comparisons, Table 12 presents

Table 11:

Primary Analysis Comparing All Three Dependent Variables
Final Models with IV and All Controls
Florida Airports Only

Variable	Model 5: Full Model, Total Eco_Impact *Standardized Beta*		Model 10: Full Model, Jobs *Standardized Beta*		Model 11: Full Model, Payroll *Standardized Beta*	
(Constant)						
Dummy_Florida	n/a		n/a		n/a	
Serv - Longest Runway (Ft.)	0.443	**	0.440	**	0.424	**
Serv - D - Airport in NPIAS List	0.202	**	0.170	**	0.212	**
Geo - Distance to CBD (Miles)	-0.085	~	-0.062		-0.080	
Base - Multi-Engine AC	0.137	**	0.135	*	0.120	*
Ops - GA Transient	0.171	**	0.195	**	0.193	**
Comp - Number Runways, 15-Mi.	-0.013		-0.005		-0.015	
Cen - Log, Eco_Intensity, 15-Mi.	0.225	**	0.241	**	0.244	**
IV_D_ Med OperCntl	0.029		0.029		0.026	
IV_D_ High OperCntl	0.171	**	0.168	**	0.164	**
F	F(9,84)=45.910	**	F(9,84)=40.766		F(9,84)=42.450	
R2	0.818		0.816		0.82	
Adjusted R2	0.799		0.796		0.8	
Average VIF for the Model	1.564		1.547		1.564	

** Indicates significance at 0.05.* *** Indicates significance at 0.01*

three versions of the model of *DV_Log_Total_Eco_Impact*: and Table 13 presents the three dependent variables (all transformed as natural logs). One notable addition to these models is a categorical variable designed to capture any variance in the data due to any unmeasured idiosyncrasies or perturbations in the Florida economic impact study. The dummy variable for Florida approached significance with one dependent variable (*DV_Log_Total_Jobs*) but not

Table 12:

Validation Analysis
Dependent Variable: DV_Log_Total_Eco_Impact
Using All Controls and Measuring the Effect of IV
Using Airports in All Three States

Variable	Model 7: Base Model with Controls Only *Standardized Beta*		Model 8: Full Model with I.V. *Standardized Beta*		Model 9: Full Model with Negative I.V. *Standardized Beta*	
(Constant)						
Dummy_Florida	0.006		0.008		0.014	
Serv - Longest Runway (Ft.)	0.543	**	0.486	**	0.506	**
Serv - D - Airport in NPIAS List	0.152	**	0.154	**	0.155	**
Geo - Distance to CBD (Miles)	-0.110	**	-0.113	**	-0.113	**
Base - Multi-Engine AC	0.188	**	0.179	**	0.188	**
Ops - GA Transient	0.166	**	0.162	**	0.147	**
Comp - Number Runways, 15-Mi.	-0.042		-0.041		-0.046	
Cen - Log, Eco_Intensity, 15-Mi.	0.210	**	0.211	**	0.207	**
IV_D_ Med OperCntl			-0.002			
IV_D_ High OperCntl			0.104	**		
IV_D_ Low OperCntl					-0.083	*
F	F(8,209) = 79.892	**	F(10,207) = 65.777	**	F(9,208) = 72.450	
R2	0.754		0.761		0.758	
Adjusted R2	0.744		0.749		0.748	
Average VIF for the Model	1.496		1.553		1.542	

** Indicates significance at 0.05.* *** Indicates significance at 0.01*

the other two. This refutes the concern that the Florida economic impact study had certain unique characteristics or operationalizations which may have distorted the outcomes. Other variations are minimal, suggesting the hypothesized effects are supported by the data.

As a general observation, it is unexpected that two "Services" cluster variables are included in the final models. The first is the length of the longest runway at each focal airport,

Table 13:

Validation Analysis Comparing All Three Dependent Variables
Final Models with IV and All Controls
Including Airports from All Three States

Variable	Model 5: Full Model, Total Eco_Impact *Standardized Beta*		Model 12: Full Model, Jobs *Standardized Beta*		Model 13: Full Model, Payroll *Standardized Beta*	
(Constant)						
Dummy_Florida	0.008		0.069	~	-0.006	
Serv - Longest Runway (Ft.)	0.486	**	0.466	**	0.469	**
Serv - D - Airport in NPIAS List	0.154	**	0.125	**	0.159	**
Geo - Distance to CBD (Miles)	-0.113	**	-0.093	**	-0.115	**
Base - Multi-Engine AC	0.179	**	0.156	**	0.165	**
Ops - GA Transient	0.162	**	0.160	**	0.176	**
Comp - Number Runways, 15-Mi.	-0.041		-0.033		-0.039	
Cen - Log, Eco_Intensity, 15-Mi.	0.211	**	0.249	**	0.234	**
IV_D_ Med OperCntl	-0.002		0.013		-0.006	
IV_D_ High OperCntl	0.104	**	0.130	**	0.105	**
F	F(10,207) = 65.777	**	F(10,207)=75.990	**	F(10,207)=65.817	**
R2	0.761		0.787		0.761	
Adjusted R2	0.749		0.776		0.749	
Average VIF for the Model	1.553		1.55		1.553	

** Indicates significance at 0.05. ** Indicates significance at 0.01*

measured in feet. This is plausible as longer runways extends an aircraft's start-stop distance according to the FAA's flight planning rules (14CFR § 25.109) which means an airport can accommodate larger aircraft which can fly greater distances with more passengers. This variable carries a standardized beta between 0.466 to 0.486 which makes it the single most influential variable in all of the final models. The second variable was a dummy which tracked an airport's presence on (or absence from) the FAA's NPIAS roster, *Serv_D_NPIAS*, which denotes a highly capable airport even if it lacks commercial airline service. Both were consistently significant, *p* <.001.

The only "Geography" variable in the final models was the distance to the central business district (*Geo_Miles_to_CBD_Dist*). This variable carries a negative coefficient which implies airports are penalized by greater distances from business centers. This variable was significant in every model, with *p* values ranging from 0.008 to 0.002.

The index variable combining census and geographic data was *Cen_Eco_Intensity_15,* which was transformed into a natural log for the analysis. Looking at the raw data for 235 airports (for ease of understanding) the minimum value was $3,797,459/sq. mi. while the maximum was $203,631,563/sq. mi.; the mean was $53,617,512 with a standard deviation of $40,586,912. The effect size for the variable is substantial; a single percentage increase in economic intensity generates 0.635% additional economic impact for the community served by that airport.

Consistent with the factor analysis results, the one variable to survive in the final model from the "Based" aircraft cluster was the number of multi-engine aircraft based at each field, *Base_Multiengine*. The coefficient was positive, the standardized beta consistently in the mid-teens, and significant at 0.002 or better. Multi-engine aircraft tend to be larger, more capable, often have two-person crews and are better equipped to handle inclement weather. It is logical they would make a greater contribution to the economic impact of an airport than smaller and less-capable equipment.

The only "Operations" variable in the model is the number of operations involving transient general aviation aircraft (*Ops_GA_Visitors*). The coefficient is very small, but the standardized beta is in the mid-teens for all three models, and the variable was consistently significant with p ranging from 0.003 to 0.001. This consistency spoke to the need to retain this variable in the final model.

The three variables in the “Competition “cluster did not achieve statistical significance and yet they had strong theoretical foundation. Testing of different indices based on the competitive cluster failed to offer any useful contribution. However, because it was selected in the original factor analysis *Comp_Num_Runways_15* remained in the final models.

Testing the Independent Variables

The independent variables were categorical dummies: the conditions of “low”, “medium” and “high” *operational control* as defined by the coding rubric. The medium condition never achieved significance in any of the models, but the high condition was consistently significant, with a theoretically correct sign, and p values ranging from 0.002 to 0.018. In the final models, six of the eight control variables are significant, all of the coefficients have the theoretically proper signs, multicollinearity has been eliminated, the R^2 remains high, and the F-test is significant.

The final model portrays the variance in the economic data with a fair degree of precision and parsimony. The source for this judgment stems from six statistics used in the analysis: the R^2 statistic, the degree of change in the adjusted R^2, multicollinearity tests, the significance of the overall model, the significance and coefficients of the individual variables, and the graphical analysis of the residuals.

The original baseline model using the nine variables identified by the factor analysis produced an R^2 of 0.738, which is reasonably strong. Over the development of the final model and the inclusion of the independent variables, the R^2 changed very little, improving just a few percent. This is important because it suggests both the original theory and the data collection were sound, and the procedure used to develop the controls was reasonable.

Scholars often consider the “adjusted” R^2 scores. The purpose of the adjustment is to measure the effect of additional variables in explaining the variance. If the R^2 is diminished as variables are added, the new variables are not enhancing the explanatory power of the model. Alternatively, if the R^2 increases this implies the new variables are explaining additional variance. This is particularly important in this research with 131 possible variables, many of which can produce significant results individually.[21] In this study, the adjusted R^2 remained relatively stable across a range from 0.707 to 0.776, depending upon the control variables and the airports selected. In almost every instance, this was only a modest diminution of the actual R^2 which indicates that the model is not being inflated artificially with extraneous variables and were meaningful to the analysis (e.g., theoretical considerations, solving problems with multicollinearity).

Multicollinearity can cause coefficient estimates to fluctuate as a result of relatively minor changes in the data or the model specification. In turn, this weakens the statistical power of a regression model and the measures of statistical significance may not be stable and trustworthy. Multicollinearity was a significant concern in this analysis because many of the control variables were highly correlated (“data multicollinearity”) and some of the index variables were derived from other control variables (“structural multicollinearity”). This problem needed to be examined and resolved. For example, in the “Operations” cluster, the total aircraft operations (*Ops_Total*) was the sum of all the other types of operations at an

[21] For example, a simple regression of the *Log - Total Population 15* to *Log – Total Economic Impact* was significant: $R^2 = .292$, adjusted $R^2 = .289$, $F(1,232) = 95.913$, $p < .001$.

airport. The "Competition" cluster included *Comp_Num_Airports_15* which is highly correlated with the *Comp_Num_Runways_15*, $r(235) = .896$, $p < .001$ because most airports only have one runway. *Comp_Num_Runways_15* is, in turn, correlated to the sum all the runway lengths, *Comp_Runway_Feet_15*, $r(235) = .940$, $p < .001$. Looking at the "Census" cluster, *Cen_EmployRate_15* is the ratio of total employment divided by the total population, and strongly related to both of them: $r(235) = .487$, $p < .001$; and $r(235) = .508$, $p < .001$, respectively. Among the 131 variables in this study, the "Census" cluster carried the highest intra-cluster correlations, as high as .983. Correlations of these magnitudes can be expected to produce multicollinearity in an OLS regression. To resolve this, the variable inflation factor statistic (VIF) was monitored and variables removed and replaced, using the process described above, to keep the VIF scores within acceptable limits.

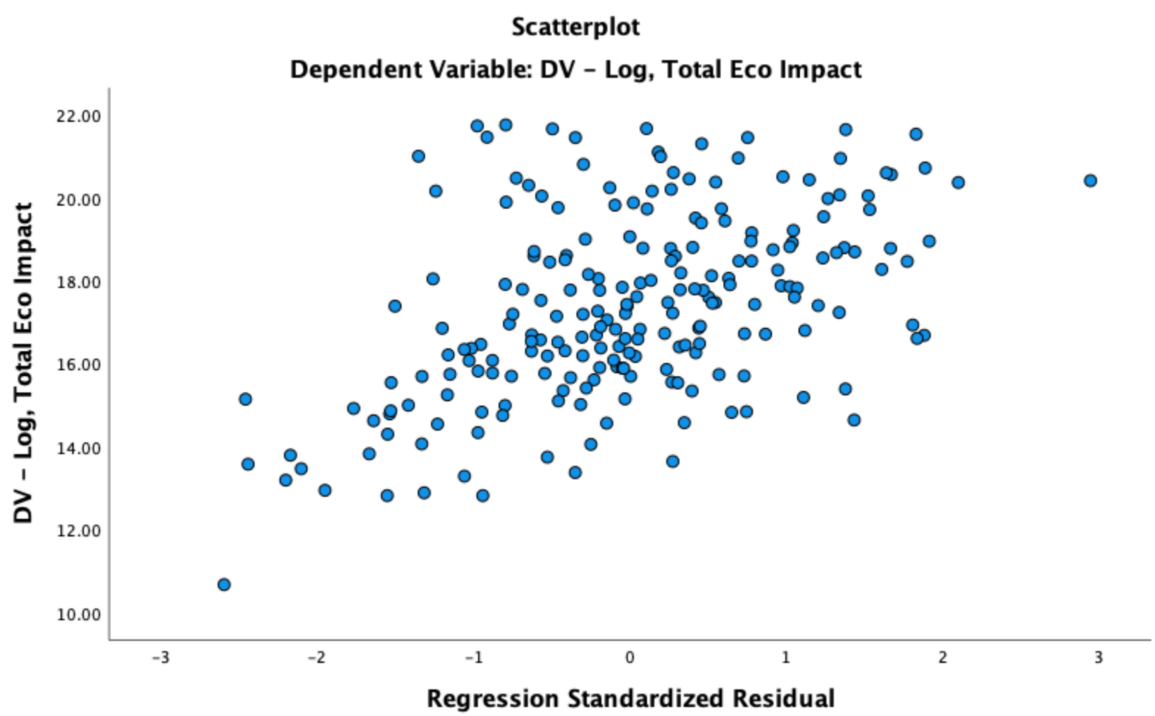
This concern was justified. The earliest models, using only the nine variables selected with the factor analysis, suffered from severe multicollinearity. Comparing the results from the Florida-only airports to the results when all three states were modeled, the coefficient for *Cen_Income_15* jumped 394% in absolute value and carried a VIF score of 105.856, far exceeding the generally accepted threshold of ten. Similarly, the coefficient for *Cen_Employment_15* tripled and carried a VIF score of 111.154. As further justification for rejecting these earliest results, in the Florida-only model six variables were significant but only four were significant in the three-state model. Across the modeling process, the instability caused by multicollinearity was resolved by substituting variables from the same cluster which were less highly correlated.

Another test of the quality and efficiency of the control variables was the significance of the overall model. The F-test for the overall models gradually improved from 17.08 in the first iteration (the factor analysis choices) to 65.770 in the final models using the validation sample. This lends a modicum of confidence that the control variables are operating as hypothesized and the results from the model will be stable and reproducible.

Of even greater usefulness were the coefficients and significance of the individual control variables. For example, theory suggested the age of an airport (the number of years it had been in service to the community) should be a driver of economic impact. Similarly, theory and experience suggested that airline service should positively drive economic impact while higher levels of competition should have a detrimental effect on the economic impact of a focal airport. None of those three hypotheses were validated by the individual coefficients and t-tests. For example, the “Competition” cluster operationalized competing airports in three ways: the number of airports within the 15-mile catchment area, the number of runways within the 15-mile catchment area, and the sum of the length of all the runways within the 15-mile catchment area. The original factor analysis had not identified any of these three variables as being relevant, but this may have been a function of the difficulties of the factor analysis given the NPD problem described above. To that end, one “Competition” variable was retained in every analysis. However, none of them explained much of the variance and none of them achieved statistical significance.

Lastly, a final measure of the effectiveness of the controls was the graphical analysis of the residuals, specifically three different charting techniques. The first technique is demonstrated in Figure 8 which is a scatterplot of the standardized residuals, testing to see if the residuals show any adverse patterns, which might indicate a missing variable. In this case, the data appears as a random cloud of observations, which is in congruence with the assumptions of OLS regressions. Figure 9 demonstrates the widely-used P-P plot of the observed values against the expected ones. The model produces estimates which are generally linear and no significant variables were missing; the pattern was weakest when the number of cases was small such as with the Florida-only analysis.

Figure 8:



It is useful to consider the incremental complexity of the model added by using the log conversion. There is no strong reason for choosing natural log transformations as it is well-understood that natural logs and base-ten logs produce exactly the same outcomes. Either form of the model could be estimated using OLS, with equivalent results, although there is the slight advantage with natural logs in that their first differential is less complex. Gelman and Hill (2007) assert natural logs are preferred because the coefficients on a natural-log scale approximate proportional differences, which speeds interpretation. In terms of this study, the most probative outputs were the standardized coefficients which reflect the relative contribution of each variable in the model, and those are presented in Tables 1-13. For the measurement of effect sizes, however, one must return to the raw regression output and consider the unstandardized coefficients. For example, *Cen_Log_Eco_Intensity* had a coefficient of 0.635 which is the anti-log exponent for that variable. A quick formula in Excel (=2.718281828^.635) produces 1.89, which is the estimated coefficient with the transformation removed. The same process can be used to compute the effect sizes of each model. All in all, the complexity added by transforming the data is a small price to pay for being able to proceed with the analysis in compliance with the OLS assumptions. Similarly, the trivial cost of converting predicted values from their log form to natural form is a modest extra step in light of being able to explain the overall effect of *operational control* on the financial performance of the firm.

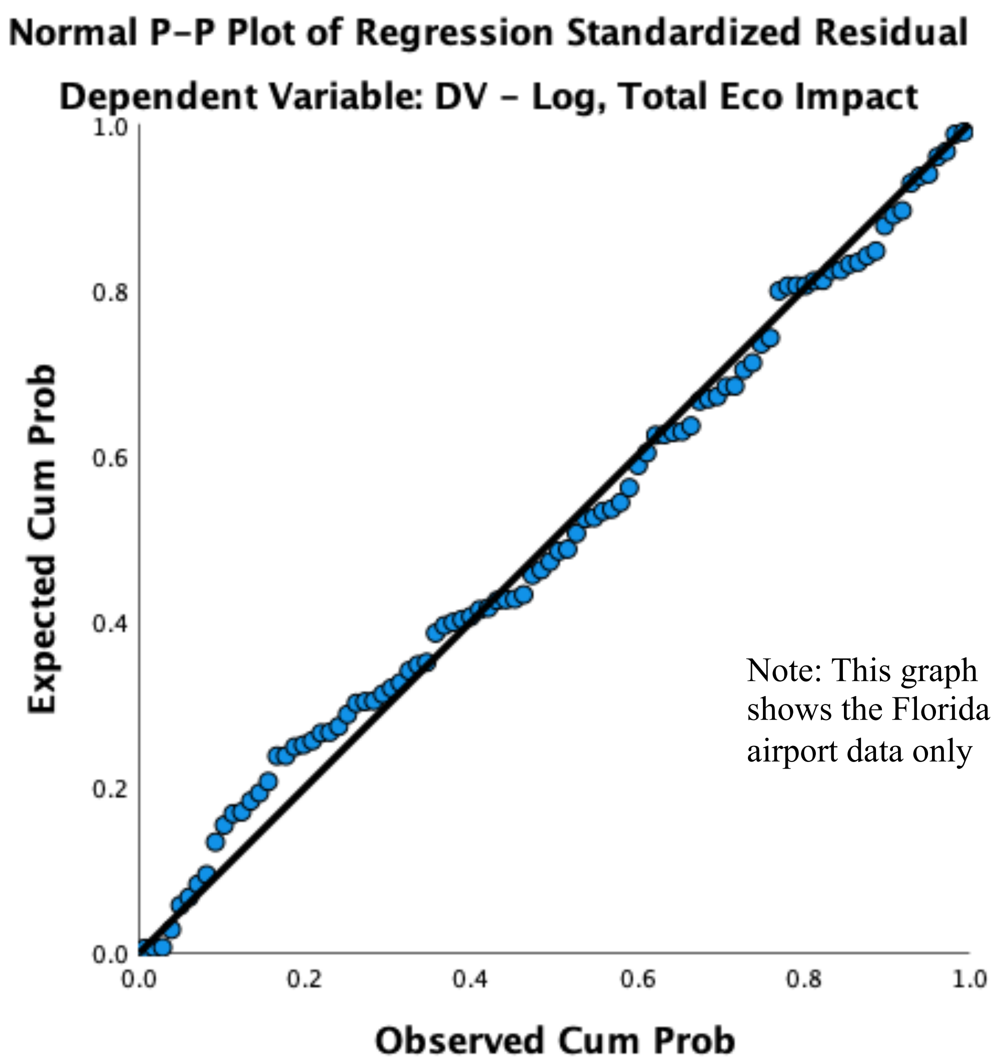
Alternative Controls

It would be prudent to investigate alternative models which might provide different results or improve the ones presented here. Of particular concern was the failure of the presence of navigable waters to be significant in any of the models (from the “Geography” cluster).

The operationalization of the navigable waters was a satellite measurement of the square miles of open aqueous surfaces within the airport catchment area (*Geo_Aqueous15*). Aqueous surfaces can be modeled on a continuum from “rare” to “abundant.” In this study, the presence of navigable waters gradually increased from a minimum of 0.35 sq. miles (Mountain Empire Airport, VA) to 694.70 sq. miles (the island airport of Marathon, FL). In the case of the Marathon Airport, 98.3% of the total surface area in the 15-mile circle around the focal airport is water, leaving little solid land for economic development. Additionally, the presence of large quantities of navigable water should be inversely correlated with altitude (Mountain Empire is at 2,558 ft. of elevation). This is confirmed by the negative, significant correlation between *Geo_Airport Elevation* and *Geo_Aqueous15*, r(235) = -.154, p = .018.

However, the correlation between *Geo_Aqueous15* and the airport's total economic impact (DV_Total_Eco_Impact) is significant only at the .10 level, r(234) = .125, p = .057,

Figure 9:



suggesting aqueous surfaces have little impact upon economic performance. This conclusion counters the author's observations of people enjoying vacations at North Carolina beaches or living in Tampa/St. Pete. Clearly proximity to lakes, rivers and beaches is attractive and should stimulate economic activity. But the final model fails to capture that condition. It is possible that aqueous surfaces might have a negatively quadratic relationship with economic performance. In that instance, the lack of any water would suppress economic activity; the presence of some beachfront would boost it; and an over-supply of water (such as at Marathon Island) would ultimately degrade economic performance. Working from that hypothesis, a model was tested including aqueous surfaces both as a linear and a quadratic effect. In neither case did it achieve significance. This is (to the author's mind) an unsatisfactory resolution and a prime candidate for further research.

Another option which seemed prudent to test were the control variables in the "Governance" cluster that had been developed during the coding process. One could question the operationalization of those variables or the possible presence of interaction effects. Two variables — *Gov_Engaged_Mngt* and *Gov_D_AA_Weak* — were added individually to the model and then in combination, first with just the Florida airports and then using all airports. In neither case was the effect significant and the additional variable(s) diluted the effects of the independent variable of *operational control*.

Looking at other "Governance" variables, another possibility was to consider the impact of the erroneous FAA data, as error-filled filings to the FAA might indicate sloppy and/or unengaged management attitudes. The variable *Gov_FAA_Data_Wrong* was added to the final model for both the Florida airports and all cases. It was significant but again had the unexpected effect of diluting the effect of the *operational control* variables

(*IV_D_High_OpCon*), apparently borrowing some of the variance the independent variable was carrying. Since this variable had no rigorous theoretical background and limited managerial implications, no further action was taken on this option.

It seemed useful to test other manifestations of managerial diligence, energy and engagement. Two items were of particular interest as they are almost diametrical opposites: the development of an industrial park at an airport could be interpreted to be the work of a diligent and energized airport management team, while the "de facto" privatization of an airport was the abrogation of almost all managerial responsibilities to a third party. The regression was run separately on both *Rubric_C2_D_IndustrialPark* and *Rubric_C4_D_DeFactoPrivate* using all the airports in the dataset. In both instances, although the coefficients carried signs in the expected directions, the results were not significant and the impact on the other variables was minor.

Lastly, because the "Services" cluster had two powerful variables in the model already, it was useful to stress-test the model by adding other "Services" variables, simply because the more services an airport offers the more attractive it will be to flyers and to businesses. Sequential tests were conducted, adding *Serv_D_ATC_Tower, Serv_D_Customs*, and *Serv_D_ContractFBO* to the models. None of these variables added any substantial new insights and none achieved significance.

Supplemental Analyses

Two supplemental analyses were performed to evaluate the efficiency of the *operational control* construct. Both involved an effort to see if the data could offer any insights to the behavior of the control variables and the independent variables over time.

The complete set of airports economic impact studies produced for North Carolina airports over the past decade was collected, dated 2012, 2015, 2017, 2019 and 2022 (for the cross-sectional analysis in this study, the North Carolina data was from the 2022 report). The ITRE analysts confirmed they used the same procedures and assumptions in all five projects, including (a) limiting their analysis to NPIAS-only airports, (b) not imputing any economic impact under conditions of missing data, and (c) using the IMPLAN input-output model. Using excel and the SPSS statistical package, it was possible to model the five outcomes across 70 airports by their degree of *operational control*. The hypothesis was that airports with a "high" degree of *operational control* (that is, having an airport authority or equivalent) would produce statistically different outcomes than airports with "low" *operational control*. For this analysis, all three of the dummy *operational control* variables ("low", "medium" and "high") were combined into a categorical string variable that the ANOVA software could accommodate.

Using a repeated mixed design ANOVA with one categorical variable, the findings of the regression analyses were generally confirmed. This involved an analysis of 68 North Carolina airports: 41 "low" airports, two "medium" and 25 "high." Lacking any data to the contrary, it was assumed that none of the airports had changed their management structure in the past decade (which would have changed their degree of *operational control*). As with the regression analyses, both GSO and SUT airports were removed as outliers for consistency. Unlike the regression studies, this data was not converted into natural logs since all five of the variables were similar (dollars of economic impact) and relatively consistent in scale (values in millions of dollars). The results were confirmatory. The Wilkes lambda statistic indicated there was no significant differences between the five time periods, so whatever economic fluctuations may have occurred over the decade did not change the economic impact results, $F(8,124) = 2.853$, $p = 0.006$. The analysis did indicate, however, that the effect of *operational control* was significant, $F(3,65) = 19.905$, $p < .001$. Another important "goodness of fit" statistic is the η^2 (eta squared) index which measures the proportion of variance explained in the ANOVA analysis by both the main effects and the interaction effects. In this instance, the η^2 score was 0.155 which, according to the rules-of-thumb suggested by Cohen (1988), indicate a large effect. A general interpretation is that the categorical variable explains 15.5% of the variance in the data, which is generally consistent with the beta coefficients found in the regression models. Figure 10 presents the data graphically while Table 14 presents the ANOVA analysis.

The second supplemental analysis was to incorporate a time-series dimension to the cross-sectional data in the original model. Included in the Geographic cluster was another variable not described earlier and not used in the primary analysis. This unused variable was a single observation for each airport reporting the change in the square miles of impervious surfaces from the first observation by the satellites (2001) until the most recent observation (2019). For example, the Gainesville, FL airport is supported by 90.730 square miles of

Figure 10:

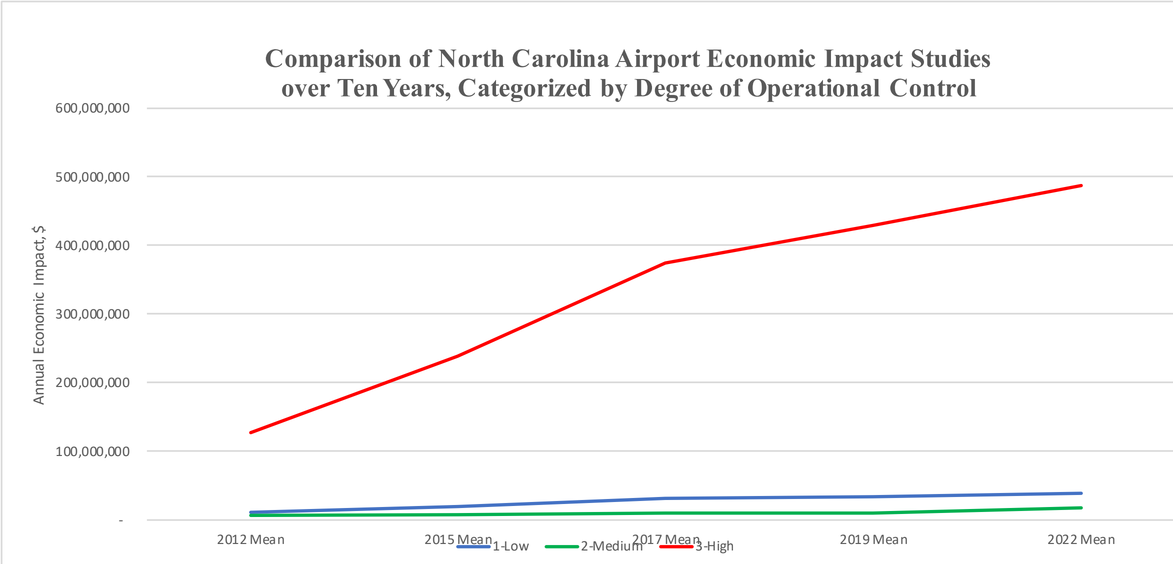


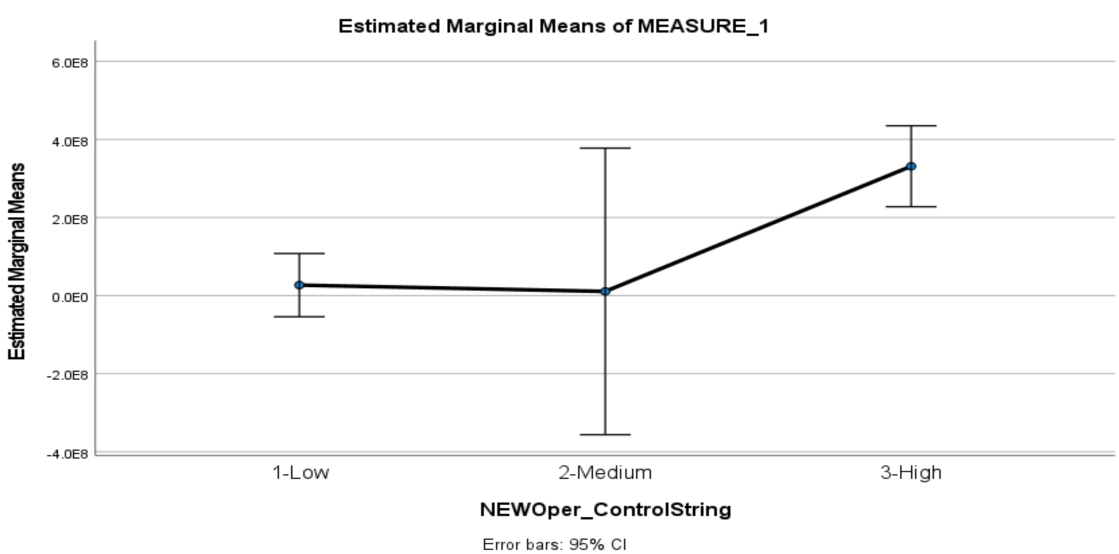
Table 14:

Mixed-Effects Repeated Measures ANOVA

MEASURE_1: Economic Impact

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[a]
Intercept	1.20762E+18	1	1.20762E+18	3.577	0.063	0.052	3.577	0.462
Oper_Control_String	7.36222E+18	2	3.68111E+18	10.905	<.001	0.251	21.809	0.988
Error	2.19422E+19	65	3.37572E+17					

a. Computed using alpha = .05



impervious surfaces amongst the 706 square miles of the 15-mile catchment area (approx. 12.8% development). Since 2001, the Gainesville area has added 8.363 square miles or 9.2% of additional impervious surfaces which puts it in the top third of all the airports in the study (Kissimmee Airport south of Orlando has the highest rate of land-use change, +23.1%, among the 235 airports in the study). It is possible that the driver of economic impact of any catchment area is influenced less by the absolute magnitude of the developed acreage and more by the rate of change in the land-use. In other words, a fast-developing region might be more economically energetic and therefore more inclined to use aeronautical services and generate greater economic impacts from that airport. Additionally, it was conceptualized that "success breeds success" and ebullient real estate markets may be self-reinforcing. An interaction effect among the land-use variables was created to test if that was the most accurate representation of the situation.

As expected, there is a strong relationship between the quantity of impervious surfaces and the change over twenty years in impervious surfaces, r(234) = .772, $p < .001$, which may suggest a problem with autocorrelation. The area of impervious surfaces also has a strong relationship with the dependent variable, *DV_Total_Eco_Impact*, r(234) = .386, $p < .001$. The relationship with the change in impervious surfaces is only slightly weaker but still significant, r(234) = .273, $p < .001$. The two geographic variables were converted to natural logs and added to the final regression model. As planned, an interaction effect (Geo_Imperv15 * Geo_ImpervDelta15) also was computed, converted to a natural log, and added to the model. Multicollinearity was detected with the direct variables which required their removal leaving only the interaction variables.

The final result is presented in Table 15 and the conclusions are ambiguous for three reasons. First, the overall model shows a strong relationship with the dependent variable when analyzing the Florida airports ($R^2 = 0.83$, $F(11,82) = 36.30$ $p < .001$) but when the dataset is validated using all the airports the relationship fades to statistical insignificance. Second, the interaction variable is not significant and carries a negative sign which conflicts with theory. Third, while the overall model is generally consistent with the full model described above the improvement in the goodness of fit is minimal. This supplemental analysis suggests while this

Table 15:

Supplemental Model with "ImpervDelta" Interaction Florida Airports Only, with IV and Controls

Dependent Variable: Log, Total Economic Impact

Variable	Model 15 *Standardized Beta*	
(Constant)		
Dummy_Florida	n/a	
Serv - Longest Runway (Ft.)	0.463	**
Serv - D - Airport included in NPIAS List	0.212	**
Geo - Distance to CBD (Miles)	-0.072	
Base - Multi-Engine AC	0.143	*
Ops - GA Transient	0.173	**
Comp - Number Runways, 15-Mi.	-0.028	
Cen - Log, Eco_Intensity, 15-mi.	0.331	**
Geo_Log_ImpervInteraction15	-0.114	
IV_D_ Med OperCntl	0.045	
IV_D_ High OperCntl	0.168	*
F	F(11,82)=36.3	
R2	0.830	
Adjusted R2	0.807	
Average VIF for the model	4.917	

** Indicates significance at 0.05. ** Indicates significance at 0.01* new land-use data is an intriguing capability and worthy of further examination it was not helpful with this model at this time.

In consideration of all these tests, it is a generally acceptable conclusion that the control variables in the final model are as efficient and yet as parsimonious as theory and data would allow.

CHAPTER 7: DISCUSSION AND CONCLUSIONS

Overall Results

This study advances the understanding of organizational design in a variety of directions, and also offers specific guidance to the owners and managers of small businesses. Starting from the most granular and expanding to the more global, these learnings can be identified as: (a) a quantified operationalization of catchment areas for general aviation airports, (b) a new operationalization of a short roster of robust control variables which “level the playing field” when comparing airports to their peers, and extends beyond traditional census data, (c) the deployment of a highly robust and replicable coding rubric which allows this study to be replicated for other states, (d) the operationalization of *operational control* as a novel and useful organizational design construct, and (e) the development of a statistically-significant model linking the organizational structure and the financial success of that organization. This final accomplishment is not trivial nor merely academic: the average “low” operational control airport generates about $33.9 million in economic impact annually. All things remaining equal, this model suggests those airports could boost that annual performance to the neighborhood of $54.2 million simply by changing their organizational structure. It is suitable here to summarize and integrate these developments.

A. Catchment Area Definition. General aviation airports are an under-studied component of the multi-modal transportation network available across the United States. As noted in Chapter 2, above, the vast majority of airport studies are performed on the 493 largest facilities in the U.S. with commercial airline service because that is where both the money and the voters can be found. This means the industry really does not know what makes a general aviation airport “tick.” The lack of research means the dynamics of smaller airports are less well-understood, best practices are poorly defined and rarely disseminated, and the political bodies which own the airports underestimate the ability of a local airport to contribute to the economic health of the community. These deficiencies generally cause local airports to be under-funded and under-managed. This study shows that for small general aviation airports the optimal catchment area for research is a circle fifteen statute miles (24.1 kilometers) in radius. This is the beginning of future research into the antecedents, behaviors and conditions which drive the success of small airports. By narrowing the focus of future research it is possible that additional studies and experiments could produce a recipe of practices and procedures which, like a rising tide, lifts all small airports to greater levels of success.

B. Identifying the Control Variables for GA Airport Studies. By examining more than 100 different variables from seven different clusters, this study was able to evaluate which control variables are the most useful in “leveling the playing field” when comparing the performance of small general aviation airports. For example, almost every airport manager dreams of the day when an airline offers service to and from their field. But this study suggests airline service is less important than the quantity of transient general aviation aircraft, so a key managerial decision might be to implement programs which make the airport more visible and attractive to transient pilots and passengers. Similarly, the presence of a large number of aircraft based at a field is helpful but the real key is having the hangars and services which specifically support multi-engine aircraft. The clarity of these findings should help airport owners and managers focus their attention on the factors which will “move the needle” of economic impact.

In terms of this study, the development and validation of the “economic intensity” variable is a particularly significant finding. Cost-benefit analyses of airport investments generally are impossible unless all of the exogenous factors surrounding an airport can be accurately controlled. This variable converts passive census and land-use data into a useful management tool. Specifically, "economic intensity" allows airport management to more precisely calibrate their efforts beyond mere population statistics. Given the level of economic intensity surrounding a focal airport, an airport may be able to use these findings to justify investments in facilities or operations, modeling the return on the investment with a fair degree of accuracy. This new control variable permits managers to make smart choices in their investments to attract new customers and/or create new economic opportunities, such as is happening at Cecil Field in Florida.

C. The Operational Control Coding Rubric. One of the key difficulties in implementing this type of cross-sectional research is devising a mechanism which allows this study to be replicated in other geographies. The coding rubric is a strong first step in achieving this goal. The rubric uses off-the-shelf, publicly available data to categorize airports by their degree of *operational control*. No special knowledge of aviation or statistics is required, merely patience and a high-speed internet connection. Using the rubric, airport managers or other researchers from across the county can evaluate the airports in which they are interested and see if the existing organizational structure is optimal for the success of that airport.

D. "Operational Control" as a Novel Construct. A large number of scholarly studies used in the development of this research explored the relationships between owners, managers, employees, vendors and customers in the environment of business operations. Individual constructs such as "leadership style", "autonomy", "governance" and "job engagement" are often deployed as factors in an organization's success. In this study, a unique construct — *operational control* — was conceptualized as a latent variable which is both an antecedent and a pre-requisite to generating that unique combination of behaviors which enhanced the economic outcomes of the organization. Three factors are germane to this study: first, the cumulative effect of those behaviors can be directly linked to the financial outcomes of the organization; secondly, the follow-on behaviors generated by the construct can be directly observed and measured, and lastly, those measured behaviors are independent of the motivations or attitudes of any one individual in the group. The statistics presented here strongly suggest that *operational control* is a useful beginning to better understanding the dynamics of any complex organization, especially those in which ownership is geographically, technically, or psychologically separated from operations.

E. Linking Organizational Design to Behavioral Outcomes. As noted in Chapter 3, above, it appears the construct of *operational control* is a moderately useful vehicle to predict the financial performance of an airport. However, it also could be used to evaluate other traits and conditions. Under conditions of "low" *operational control* one might hypothesize (a) there will be fewer airport services, (b) the services offered will be more limited (e.g., self-service fuel versus full-service), (c) the physical condition of the airport buildings and public areas will be more basic and less ostentatious, (d) the airport manager will be less likely to have professional training in airport management, (e) the airport manager will be less likely to participate in airport association meetings and seminars, (f) the airport employees will be less likely to utilize voice to promote organizational improvements, (g) employees will exhibit less job engagement, (h) employees are more likely to be represented by a labor union, and (i) airport employees will have less independence in operational matters such as marketing, pricing, human resources, purchasing, payables, banking, legal representation, benefits, incentives and compensation. Any one of those conditions could be very important as they would degrade an airport's ability to generate substantial economic impact. These questions will require further research and richer, more personalized data sources for their resolution.

F. Linking Organizational Design to Financial Outcomes. As noted in Chapter 2, and explored statistically in Chapter 6, above, very few scholarly papers have directly tested the link between an organizational structure and the financial success of the focal organizations. Most papers only study a portion of that journey, linking organizational structures to intermediate accomplishments such as customer satisfaction or customer retention, which are assumed to indirectly improve financial outcomes. This study makes no such assumptions. This study is almost unique in that it explicitly "closes the loop" and links the presence (or absence) of a specific organizational design directly to the success (or failure) of the economic outcomes of the organization through the construct of *operational control*.

Specifically, the coefficient for "high" *operational control* was large and statistically significant in virtually every model and every state. Table 16 quantifies the impact of this effect size. In the "Starting Condition" portion of Table 16, the three degrees of *operational control* segment the 219 airports which were used in the three-state validation regression.[22] There were three dependent variables: the jobs created, the payroll generated, and the total economic impact. The table shows that the airports in this study generated 368,000 jobs, $20 billion in payroll and $65 billion in total economic impact. Those values are then averaged to produce a hypothetical "typical" airport of low, medium and high *operational control*. The typical "low" airport would produce 224 jobs, $10.9 million in payroll and $33.4 million in total economic impact, or about 4.8% of the economic output of the "high" airports. The second part of Table 16 is termed the "treatment" condition. Keeping all other factors

[22] Pairwise-deletion of cases with missing values reduced the n from 235 to 219 in some of the regressions.

unchanged, it demonstrates the effect of changing a “low” airport to a “high” condition, as presented in the red box. The number of jobs jumps to 45,071; the payroll swells from $1.3 billion to over $2 billion, and the total economic impact jumps from $3.9 billion to almost $6.3 billion, a 60.2% increase. Importantly, these benefits arise only from the 116 airports in this study.

Consider if this effect were multiplied across the United States. It appears that 52.9% of the airports in this sample fit the criteria of “low” *operational control*. There are 3,300 airports in the NPIAS system, so one might estimate that 1,700 or so of those airports also share the “low” organizational design. If the average “low” airport is producing $33.9 million in economic impact, the cumulative national total for “low” airports approaches $59.2 billion. Moving those airports to a “high” condition could open a pathway for those airports to

Table 16:

The Economic Impact of Airport Changing from "Low" to "High" Operational Control

STARTING CONDITION

Degree of Operational Control	# Airports	All Airports, Total_Jobs	Average Airport, Total_Jobs	All Airports, Total_Payroll	Average Airport, Total Payroll	All Airports, Total Econ Impact	Average Airport, Total Econ Impact
1-Low	116	26,030	224	$ 1,264,251,000	$ 10,898,716	$ 3,928,141,000	$ 33,863,284
2-Medium	17	15,360	904	$ 698,231,000	$ 41,072,412	$ 2,090,759,000	$ 122,985,824
3-High	86	327,548	3,809	$ 18,121,291,000	$ 210,712,686	$ 59,514,964,000	$ 692,034,465
Grand Total	219	368,938		$ 20,083,773,000		$ 65,533,864,000	

TREATMENT CONDITION

Degree of Operational Control	# Airports	All Airports, Total_Jobs	# Jobs If "Low" Airport Switches to "High"	All Airports, Total_Payroll	$ Payroll If "Low" Airport Switches to "High"	All Airports, Total Econ Impact	$ Total Econ Impact If "Low" Airport Switches to "High"
1-Low	116	26,030	45,071	$ 1,264,251,000	$ 2,012,705,530	$ 3,928,141,000	$ 6,291,290,936
2-Medium	17	15,360	15,360	$ 698,231,000	$ 698,231,000	$ 2,090,759,000	$ 2,090,759,000
3-High	86	327,548	327,548	$ 18,121,291,000	$ 18,121,291,000	$ 59,514,964,000	$ 59,514,964,000
Grand Total	219	368,938	387,979	$ 20,083,773,000	$ 20,832,227,530	$ 65,533,864,000	$ 67,897,013,936
Among "Low" Airports, % Change Made Available by Switching:			73.2%		59.2%		60.2%

Regression Results (From Table 13)

D.V.	Coefficient Based on Natural Log	Effect Size After Anti-Ln Conversion
Jobs High	0.549	1.732
Pay High	0.465	1.592
Eco_Impact High	0.471	1.602

achieve their potential, which would be in the range of $94.8 billion. For airports as an industry, this is important because — for all the reasons discussed earlier in this paper — the traditional corporate financial measures of profit and loss are neither suitable nor even available. But this finding is equally important for non-aeronautical organizations which seek to do a better job achieving their organizational goals. The learning from this research suggests there is a specific organizational structure which, for the first time, allows managers to pick a target, measure the tasks to be performed to reach that target, and then manage to that goal if the parent organization or supervisors will simply allow them to get on with the job.

Limitations of the Study

As a regression study, the relationships described in this analysis are correlational and no attempt to prove causation is attempted. For example, these regression models suggest longer runways lead to greater economic impact. But which came first? Perhaps a healthy and affluent local economy is better able to fund longer runways (that is, the local economy demands the service and can afford the construction costs). Alternatively, perhaps long runways come first (as a consequence of surplus military resources, perhaps) and, as a result, that extra capability brings more visitors and more businesses to produce healthier economic ecosystems. This study is not structured to disentangle that cause-and-effect relationship.

Another limitation of this study is the focus on just three states and 235 airports. These states were selected because they had relatively recent economic impact studies computed using similar procedures and based upon the IMPLAN input-output model. But all three states are densely populated, all are generally prosperous, enjoy relatively benign weather, are heavily dependent upon tourism, have excellent road systems, and border the Atlantic Ocean.

One might envision other economic zones having different expectations of their airports. For example, states less reliant on tourism might cast a more skeptical eye on the funding of their airports. Alternatively, more mountainous zones might place a greater value on aviation services simply because ground-based travel is more difficult. An economic impact analysis of airports across Alaska or even just the northern tier of the U.S. — where distances are greater, and winters are unflyable — might produce different outcomes than those discerned in this study. Broadening the study to include western states or even airports in Canada, the United Kingdom, Australia, and New Zealand would be a profound extension of this study and improve the generalizability of the findings.

In terms of the IMPLAN model, despite the efforts to control for state-by-state variations in the collection and modeling of economic impact data, there can be no doubt that there were differences between the states and their studies. As noted earlier, the Florida study included every airport which returned a survey including non-NPIAS airports and even airports with no land-based runways at all. North Carolina researchers limited themselves exclusively to NPIAS-listed airports. To delve more deeply into the research goals, motivations, techniques and assumptions of each states' economic impact report would be very interesting and perhaps allow the development of a subtler control variable(s) than merely the state-by-state code tested in this study.

While airports and communities change slowly compared to other industries and markets, they do evolve. Technological advances also have allowed the aviation industry to make remarkable improvements in efficiency, environmental performance, and safety. Yet this study lacks ability to quantify any of those dynamics over a prolonged period. Indeed, this study was specifically designed to minimize temporal effects (except for the two supplemental analyses noted above) simply because operationalizing such large-scale effects would be prohibitively complex. For example, during the time period of this study (a) the COVID crisis occurred, (b) Russia attacked the Ukraine igniting inflation in fuel costs, and (c) the Boeing 737 Max suffered two severe crashes which took hundreds of airplanes out of the commercial airline fleets. The ramifications of these conflicting pressures are unmeasured in this study, which is the reason this study is limited to relatively recent and highly comparable economic impact studies.

The last major limitation of this study is the lack of information regarding the human side of airports. Airport management is a human endeavor and subject to all the vagaries of personalities, ambitions, skills, and perceptions. One does not have to be a trained psychologist to suspect the aspirations of the politicians running a county government might have very different expectations and aspirations for the airports they run when compared to the actual airport managers and any airport authorities. Airport managers might be seeking new posts at bigger airports and that ambition may undermine their focus on the airport at which they currently serve. Airport authorities usually are staffed by volunteers, usually political appointees, who may or may not have the energy, technical skills or even the time to delve deep into airport issues. These complexities are beyond the scope of this study but, it is hoped, might be an enticing subject for future analyses.

Opportunities for Further Research

Research into the organization, politics, performance, and human-factors of small airports is fertile ground for organizational design and organizational behavior researchers. First and foremost, airports are operationally consistent, plentiful in number, geographically diverse, and rich secondary data sources are available. In terms of this study, the highest priority could be given to efforts to expand the dataset to include more airports in additional states, which would improve the generalizability of the results and add nuance to the statistical findings.

A slightly more challenging body of work could be to expand the research to include different input-output models. Perhaps there is something unique about the IMPLAN model which distorts the data in an unknown manner. Perhaps the assumptions, data collection processes, agency budgets or political pressures on the researchers are elements which could be tabulated and incorporated into a multi-stage regression model.

The question of competitive intensity is still unresolved. It may be possible to develop an index of competitive intensity, something akin to the well-known Herfindahl–Hirschman Index (HHI) of market concentration, using the operational data from the FAA. The HHI index uses market share as the operationalization of competition, and from the FAA data one could compute the "market share" of an airport in terms of take-offs and landings. This may prove to be more effective than the "runway length" competitive measures used in this study.

Regarding the coding rubric, it would be useful to measure the consistency and stability of the coding results across different raters. The calculation of Cronbach's alpha for the coding rubric would be very useful. One technique to accomplish this might be to use a group of students in an aviation program to evaluate a randomly selected group of 30 or 40 airports to measure the congruence of their ratings. Long-term, it would be probative to determine if more quantifiable variables could be used to convert the nominal *operational control* construct into a richer ratio-scale variable.

In a similar mode, a very useful extension would be to refine the twelve Governance variables deduced from airport web sites and to measure their consistency across different raters. For example, two of the variables simply do not apply to airports which are not managed by airport authorities, which artificially deflates the Governance indices for those airports. Additionally, some airport web sites are not easy to navigate. It is possible that certain behaviors measured in the Governance cluster — such as publicizing the minutes of airport authority meetings — are buried in a remote corner of an airport web site where some reviewers might locate them while others might not. The development of Cronbach's alpha for the Governance scale would enhance its reliability and validity.

An important expansion of this study would be to improve the understanding of the impact of possible moderators. The two most likely candidates to be moderators are (a) the quantity of navigable waters in the airport catchment zone and (b) the rate of change in the quantity of impervious surfaces in the catchment zone. This study found no instances in which the aqueous surfaces condition was significant, and yet finding that is contradicted by the crowds and businesses along the Florida shoreline. It seems reasonable that some operationalization of proximity to lakes and/or oceanfront could quantify the economic value of beachfront properties. Other moderator candidates might be the number and value of the grants an airport receives from the State or the Federal government.

Personalities might come into focus with additional studies. It would be highly useful to profile airport managers and determine if they have specific traits (e.g., an engineering degree, flying experience) or behaviors which differentiate the weak performing airports from the stronger ones. At least four possibilities come to mind, including (a) the personality traits of airport managers, using the Big Five personality traits documented in numerous other studies, (b) the Job Autonomy of an airport manager, (c) the job engagement of an airport manager, an Airport Authority, or even the staff of the different airports, and (d) the leadership styles of the airport managers. For example, perhaps job engagement enhances the performance of an airport manager and might even overwhelm the deficiencies of a weak airport authority, or job engagement might be a moderator of the link between *operational control* and economic output, enhancing or decreasing the economic impact of the airport.

This study makes no claim to causality and simply documents an observed pattern in the performance of airports. However, it would be very interesting to deploy a quasi-experimental approach to see if causality could be determined. It might be possible to perform a difference-in-differences test by comparing airports over time between when the airport operated in a condition of “low” *operational control* and then switched to having an Airport Authority which would move the airport to the “high” *operational control* condition. This author has no information about the frequency of such transformations, but over the thousands of airports in the U.S. there must be at least a few dozen which have made the change in the past decade. A sample of that sort might be a sufficiently large sample to develop a statistical model.

Another future study could segment an airport data set into two extremes, ignoring the “medium” *operational control* condition. This analysis is based on the concept that the subtle relationships predicted in this analysis may be obscured if the sample size is inflated with average-performing airports because those firms might dilute the hypothesized relationships (Doty, Glick & Huber, 1993). This decision follows a broad body of literature in which samples were segmented to highlight the variance. For example, White (1986) studied 69 business units and found significant results by polarizing the study into high/low performing firms. Firth, Fung and Rui (2006) split their sample between bottom-quartile low-performing firms and high-performing firms which were in the top quartile. Lenz (1980) also segmented his sample of eighty savings and loan associations based on their three-year return on average assets, which resulted in the identification of 24 firms in the high-performance group, 26 firms in the low-performance group; notably 30 firms were excluded from further analysis. In a similar bifurcation, Khandwalla (1973) segmented his study of 79 manufacturing companies into two groups, high- and low-performing. Olson, Slater and Hult (2005) compared the success of generalized corporate strategies by examining only the top third of firms in their study. It is anticipated that by studying the extremes a more accurate and stable model will be produced. In effect, the "low" group would be the control group and the "high" group would be the treatment group.

Similarly, it would be very interesting to build a model that allows airports to define peer airports in a systematic manner. Peer-comparisons are very interesting because it allows the management of the airport to compare organizations, staffing, policies, prices, capital improvement plans and other crucial decisions with other organizations facing similar problems with similar resources. Today, most peer analyses are performed on rudimentary criteria selected in an ad hoc manner (e.g., length of longest runway, the presence of commercial service) and without theoretical underpinnings. Once a group of peer airports is defined, perhaps using cluster analysis or propensity matching, ANOVA or chi-square analyses could determine if the economic impact of peer airports can be differentiated, say for example, by their management structure.

Conclusions

While it would be presumptuous to assert this is a pioneering study, it is unique in four dimensions. First, the focal subjects of the research — small airports in the U.S. — are a rarely explored group of small businesses that demonstrably offer many attractions to researchers (a large population, highly accessible, numerous consistently-measured and quantifiable operating parameters, and so on). By standardizing on one industry with highly similar operational procedures, this study establishes a template which can be used and refined by other researchers and provides a benchmark for future organizational design studies. Secondly, the data collection and amalgamation in this research was unique. The combination of different data sources represents a useful extension of new "big data" capabilities from satellite, census data, air traffic systems and self-reported statistics. A future extension using "web scraping" software could enhance this analysis by automating the Governance variables or assembling new information regarding customer satisfaction. A third unique dimension incorporated in this study is the development of a statistical link directly binding an organizational design to financial outcomes. This study is one of the very few known to this author which conclusively links an optimal organizational design directly to improved financial outcomes. In particular, this study shows that an airport can boost the number of jobs it produces by 73.2%, boost the payrolls relying on the airport by 59.2%, and boost its overall economic impact by as much as 60.2% with a simple change of the organizational chart. Lastly, and most generally, this study has advanced the understanding of the dynamics of businesses or organizations operating under the burden of distal and diffident ownership. The findings suggest that organizations operating in that mode can improve their performance significantly if the authority they need to perform their duties can be delegated with merely minimal oversight.

In terms of specific accomplishments, this study identified and quantified certain research parameters (catchment area size and control variables) which will be helpful to future researchers in the aeronautical industry and perhaps in others such as retailing or public services. This study has laid the groundwork for additional research such as bringing well-known constructs (such as the Big Five Personality traits, autonomy, leadership measures, and job engagement) which could be implemented in future studies with a goal of bringing more nuanced understanding to these questions. This study also introduced the possibilities of time-series analyses or even quasi-field experiments in this field which could establish causality. Perhaps most importantly, this study offers airport managers and politicians a concrete managerial strategy backed by a strong rationale which will improve the management of small airports and aid the communities they serve.

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APPENDICES

Appendix 1: Recent U.S. Airport Economic Impact Studies

State	Date of Report	Uses MPLAN	# Airports (Incldg Coml.)	Gross Eco Impact ($M)	State	Date of Report	Uses MPLAN	# Airports (Incldg Coml.)	Gross Eco Impact ($M)
Alabama (?)	n/f				Montana	2016		78	$ 2,779
Alaska	2019		394	$ 3,600	Nebraska	2019	Y	79	$ 8,600
Arizona (1)	2011	Y	83	$ 20,494	Nevada	2003	Y	28	$ 368
Arkansas	2019		90	$ 3,564	New Hampshire	2013	Y	12	$ 1,245
California	n/f		-	-	New Jersey	n/f			
Colorado	2020	Y	74	$ 4,860	New Mexico	2017	Y	60	$ 2,610
Connecticut	n/f				New York	n/f			
Delaware *	2018		11	$ 1,120	North Carolina (3)	2019		72	$ 52,384
Florida	2019	Y	129	$ 162,745	North Dakota	2015	Y	89	$ 127
Georgia (2)	2019	Y	103	$ 73,697	Ohio	Requested			
Hawaii	n/f		-	-	Oklahoma	2015	Y	109	$ 10,627
Idaho	2020	Y	68	$ 4,855	Oregon	2016		57	$ 28,497
Illinois	n/f		-	-	Pennsylvania	2019		127	$ 28,500
Indiana	2012	Y	69	$ 14,101	Rhode Island	Requested			
Iowa	n/f		-	-	South Carolina (4)	2018	Y	57	$ 897
Kansas	2016	Y	73	$ 9,033	South Dakota	2020	Y	56	$ 1,270
Kentucky	n/f				Tennessee	2019	Y	78	$ 20,588
Louisiana	2019	Y	68	$ 9,318	Texas	2020		289	$ 94,300
Maine	2019	Y	36	$ 1,504	Utah	n/f			
Maryland	2018		35	$ 1,581	Vermont	2021	Y	16	$ 525
Massachusetts (3)	2019		39	$ 24,692	Virginia	2018	Y	66	$ 22,850
Michigan	n/f				Washington (5)	2020	Y	134	$ 107,000
Minnesota	n/f				West Virginia	2021	Y	24	$ 816
Mississippi	Undated	Y	73	$ 2,533	Wisconsin	n/f			
Missouri	2012	Y	99	$ 11,101	Wyoming	2020	Y	34	$ 1,852
					Total:			2,909	$ 734,633

Notes:
(1) Results distorted by large military presence included in the study
(2) Distorted by Atlanta-Hartsfield, which contributed 85% of the impact
(3) Reports the use of a "multiplier effect" but does not document the methodology
(4) Excludes the impact of Boeing, a huge employer in the Charleston SC area
(5) Includes the iimpact of Boeing, a huge employer in the Seattle area

The author has collected 42 executive summaries of state airport studies encompassing 2,800 airports with $734 billion in economic impact, plus three additional studies for Canada, the UK and Australia. The oldest report is from 2003 (Nevada) and the most recent ones are from 2021 or 2022 (North Carolina, Vermont and West Virginia); oddly, one is undated. Data from North Carolina is available for 2012, 2015, 2017, 2019 and 2022. The focal analysis in this study used the 2022 North Carolina data. 26 reports use the FAA-approved IMPLAN econometric model. Alaska and Texas have the most airports and New Hampshire has the fewest, although several states include non-traditional facilities such as seaplane bases and airports with grass runways. Nevada has the lowest GA economic impact at $368 million and Florida has the greatest economic impact at $162 billion. A detailed review has found several factors which make some studies not comparable to others. For the purposes of this study, only general aviation airports (that is, those minimal commercial air service) from states producing comparable economic impact studies will be included.

Appendix 2: Typical Airport Manager Survey Used in Input-Output Models

NORTH CAROLINA AVIATION ECONOMIC CONTRIBUTION STUDY

Calendar Year 2021 Data Request Survey for General Aviation Airport Management

The N.C. Department of Transportation Division of Aviation requests your assistance in completing an analysis of the economic contribution of aviation in North Carolina, and more specifically, how important your airport is to its community. By providing this information, you will be ensuring that your airport's economic contribution will be properly calculated. This study will use data from calendar year 2021. Results of the study will be provided to you. We anticipate this study will be completed by early 2023.

Please complete the survey and return it to Daniel Findley, Daniel_Findley@ncsu.edu, by Monday, May 16, 2022. If you have any questions feel free to contact Daniel Findley at Institute for Transportation Research and Education, Daniel_Findley@ncsu.edu, or Amanda Conner at the Division of Aviation, aconner1@ncdot.gov or 919.618.2051

1 AIRPORT NAME — **MOORE COUNTY** — **SOP**

Orange shaded cells denote places where your input may be needed.

Contact Information

Name:	Ron Maness
Address:	7825 Aviation Dr., Carthage, NC 28327
Email Address:	airportmanager@airport.com
Phone Number:	(910) 692-xxxx

2 AIRPORT USE

We have used official data for your airport that has been reported on FAA Form 5010 to estimate the number of aircraft and aircraft operations during the last year for which a report is available. This information will be used to estimate visitors to your airport and tax impacts of your airport. If these statistics for current numbers of based aircraft and annual number of aircraft operations are accurate, please skip to Question 3, otherwise, make the appropriate revisions where necessary in the tables below based on your revised estimates for calendar year 2021.

CURRENT NUMBER OF BASED AIRCRAFT		
	5010 Data (Based On Your Most Recent State or Federal Inspection)	Statistics Based on Your Revised Estimates for 2021
Single Engine	63	91
Multi Engine	9	12
Jet	3	3
Helicopters	0	2
Gliders	0	
Military	0	
Ultra-Light	0	
Total Aircraft	75	108

ANNUAL NUMBER OF AIRCRAFT OPERATIONS		
	5010 Data (Based On Your Most Recent State or Federal Inspection)	Statistics Based on Your Revised Estimates for 2021
Commercial	-	
Commuter	-	
Air Taxi	2,384	3,568
General Aviation:		
Local	10,976	38,484
Itinerant	3,958	4,716
Military	136	523
Total Operations	17,454	47,291

COVID IMPACTS - Describe any impacts to the economic impacts of your airport related to COVID (positive and/or negative impacts).

Covid had a significant negative impact on fuel sales early in our fiscal year. However sales increased late in the year and exceeded projections

3 BASED AIRCRAFT

If aircraft at your airport pay propety tax to a city/cities, please list the city and the property tax rate (for 2021).	n/a
If aircraft at your airport pay propety tax to a county/counties, please list the county and the property tax rate (for 2021).	Moore County .755

If you know of an online resource or a contact in your local tax office who can help us locate this information, we would greatly appreciate your assistance.

Gary Briggs, Tax Administrator, Moore County, xxxxx@countync.gov (910) 947-xxxx

4 AIRPORT REVENUES: SALES OF GOODS AND SERVICES

Type of Goods/Services	Total Sales
Food and Beverage	$ -
Retail (gifts, news, merchandise, etc.)	$ 3,357
Rental Car	$ -
Services Subject to Sales Tax*	$ -

*** Service contracts: a warranty agreement, a maintenance agreement, a repair contract, or a similar agreement or contract by which the seller agrees to maintain or repair tangible personal property.**

Airport Revenue	Total Revenue		
Rental or Lease of Hangar/Land/Office Space	$ 467,236		
Aircraft Fees (tie downs, ramp fees, landing fees, etc.)	$ 207,703		
Other Revenue (please describe)	$ 6,303	**Description of Other Revenue**	Dish Washing & Misc.
Other Revenue (please describe)	$ 20,475	**Description of Other Revenue**	Call Out Fees
Other Revenue (please describe)	$ 20,445	**Description of Other Revenue**	Ground Power Unit (GPU)
Other Revenue (please describe)	$ 64,800	**Description of Other Revenue**	Car Rental Agency
Other Revenue (please describe)	$ 6,238	**Description of Other Revenue**	Rental Car Fuel
Other Revenue (please describe)	$ 3,215	**Description of Other Revenue**	Oil Sales
Other Revenue (please describe)	$ 8,125	**Description of Other Revenue**	Lav Services

Type of Fuel	Total Sales*	Total Gallons*
AvGAS	$ 531,891	**102,380**
JetA	$ 3,445,482	**676,527**

*** If only one data set is available (sales or gallons), please complete whichever one is known.**

5 AIRPORT BUDGET / EXPENSES

Please complete the budget table for your airport in calendar year 2021 (include all airport expenses - personnel, capital projects, maintenance, administration, as applicable). If you have an airport specific budget, you can send us that information instead of completing these questions.

Budget Item	Total Expense Amount	Budget Item	Total Expense Amount

6 **AIRPORT TENANTS AND EMPLOYMENT (Located on or adjacent to airport property)**

To estimate the economic contribution of your airport we need a complete list of any firm or government entity located at the airport which conducts business of any type. Please list any firm or government entity -- owner/sponsor, FAA, FBO, airlines, air cargo, baggage, ramp services, gift shop, rental cars, limos, taxis, caterers, corporate pilots, aircraft maintenance, flight instruction, vending, restaurant, etc., which does business of any type at the airport. Input number of tenant jobs as full-time equivalent employees (i.e., two 20-hour per week employees = 1 full-time employee). Some tenant category types have already been entered into the table, please add/edit/remove as appropriate for your airport. Add rows or pages to the file if you need additional space.

Airport Owner/Firm/Organization/Tenant		Point of Contact Information			Number of Tenant Jobs
Type of Firm/Organization	Name of Firm/Organization	Name	Telephone	Email Address	
Airport Owner/Sponsor	Moore County	Wayne Vest	(910) 947-xxxx		156
FBO	Moore County Airport	Ron Mxxxx	(910) 692-xxxx		19
Rental Car	Hertz Dollar Thrifty	Kathleen Oxxxx	(910) 829-xxxx		6
Aircraft Maintenance	Pinehurst Aviation Service	Ken Hxxxx	(910) 587-xxxx		16
Flight Instruction	Sandhills Flyers	Ken Hxxxx	(910) 587-xxxx		21
Vending	Aberdeen Coca-Cola	Tony Cxxxx	(910) 690-xxxx		19
Flight Instruction	Total Flight Solutions	Phil Gxxxx	919-730-xxxx		22
Parent Group	Soverign Aerospace	Ken Hxxxx	(910) 587-xxxx		14
Govt Contractor	MAG Aero	Nate Hxxxx	(919) 353-xxxx		62
Govt Contractor	DST	Ron Fxxxx	(353) 353-xxxx		41
Air Charter	Time Saver Aviation	Ken Hxxxx	(910) 691-xxxx		8

7 **MAJOR AIRPORT USERS (For those who utilize the airport)**

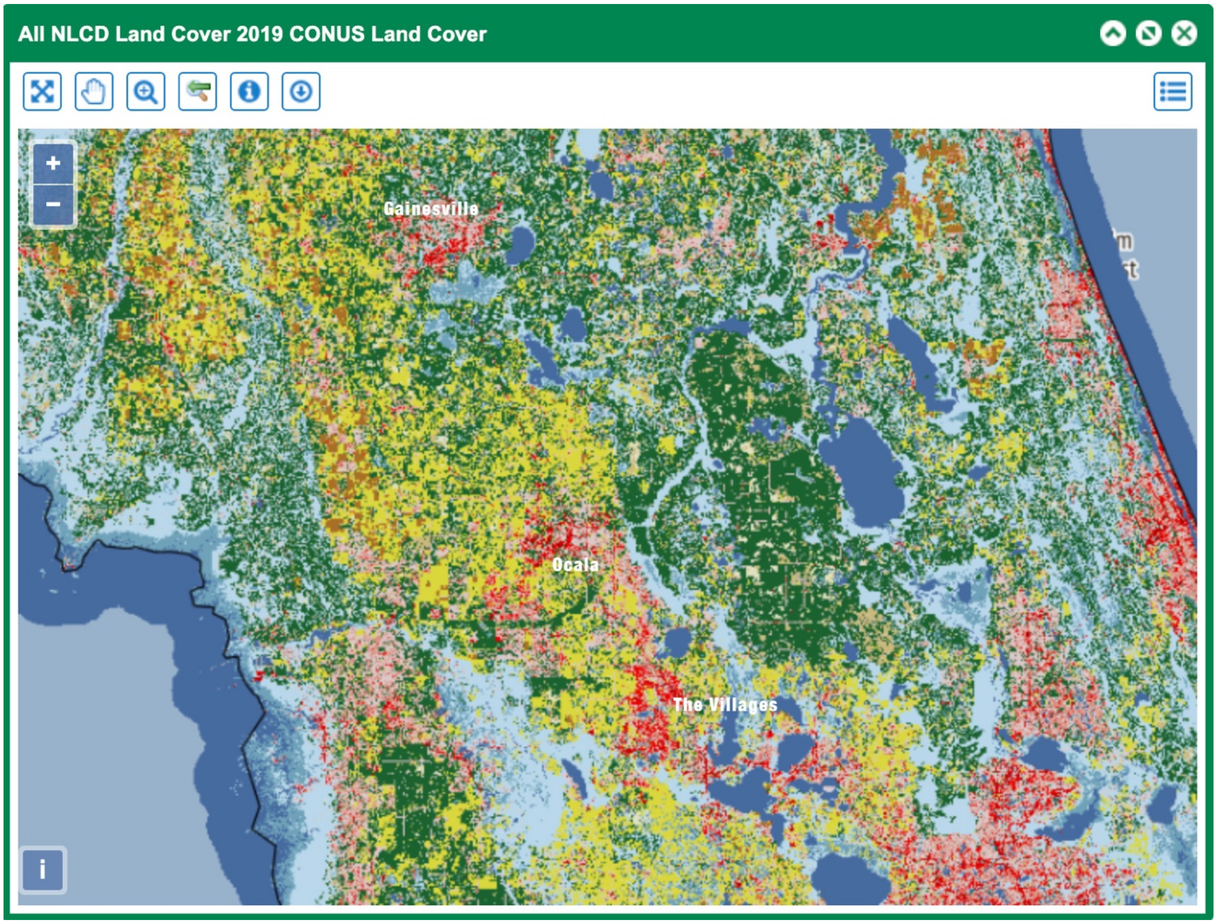
Please help us locate companies that utilize your airport. List below any companies that use your airport regularly and indicate if they have aircraft based at your airport. Please list any businesses located in your airport's service region that you feel are dependent on your airport. These could include significant air users, air freight shippers, local manufacturing companies, etc. Add rows or pages to the file if you need additional space.

Firm/Organization		Point of Contact Information			Number of Based Aircraft
Type of Firm/Organization	Name of Firm/Organization	Name	Telephone	Email Address	
Manufacturer	McMurray Fabrics				1
Golf Resort	Pinehurst Resort	Eric Kxxxx	(910) 322-xxxx		
Limo	Pinehurst Transportation -Resort	Eric Kxxxx	(910) 322-xxxx		
Limo	Kirk Tours	Marva Kxxxx	(910) 295-xxxx		
Limo	Elite Secure Transport Services	Edward Ixxxx	(910) 690-xxxx		
Limo	Eco Style	Chris Cxxxx	(919) 867-xxxx		
Chauffeured-Taxi	Safeway Taxi	William Dxxxx	(910) 528-xxxx		
Chauffeured-Taxi	Ram Transit	Dean Sxxxx	(910) 246-xxxx		
Taxi	A-Ride	Jimmy Hxxxx	(910) 986-xxxx		
Taxi	Masters Taxi	John Kxxxx	(919) 201-xxxx		
Rental Car	Enterprise	Dwayne Cxxxx	(910) 633-xxxx		
Economic Development	Partners in Progress	Natalie Hxxxx	(910) 690-xxxx		
Convention & Visitors	Convention & Visitors Bureau	Phil Wxxxx	(910) 692-xxxx		
Golf	US Golf Association (USGA)	Janeen Dxxxx	(908) 326-xxxx		
Health Care	First Health of the Carolinas	Gretchen Kxxxx	(910) 715-xxxx		
Health Care	Pinehurst Surgical Clinic	Charles Gxxxx	(910) 215-xxxx		
Community College	Sandhills Community College	Germain Bxxxx	(910) 695-xxxx		

END OF SURVEY FORM - THANK YOU FOR YOUR RESPONSES

Please return this completed form via email to: Daniel_Findley@ncsu.edu
or mail to: Daniel Findley
Institute for Transportation Research and Education (ITRE)
NCSU Campus Box 8601
Raleigh, NC 27695

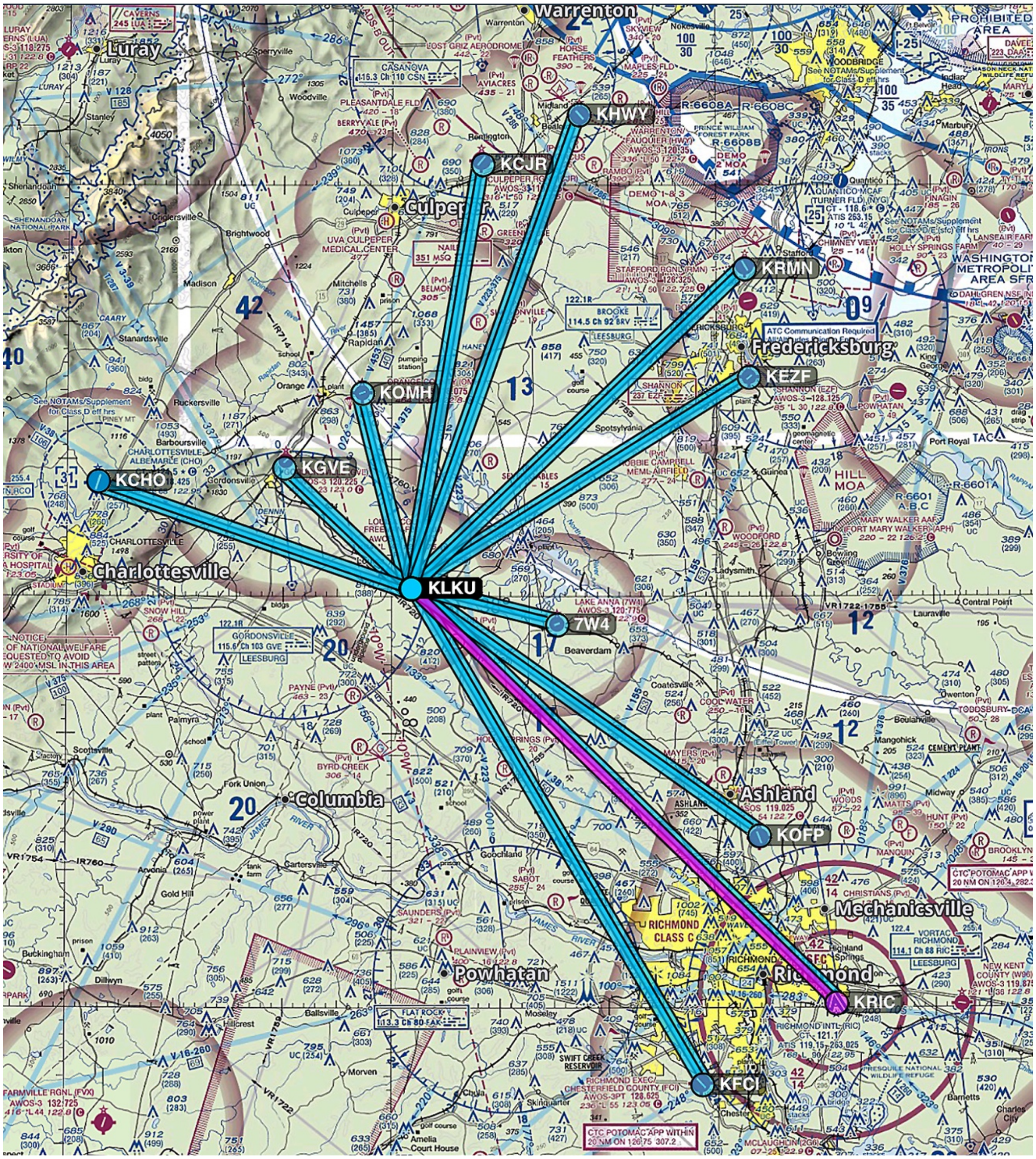
Appendix 3: Representative Example of NCLD Land-Use Imagery, 2019 Release



This image is a sample of the output from the NCLD land-use database. Different types of vegetation are depicted in shades of green and yellow, aqueous surfaces are blue and impervious surfaces — a variable used in this study — are depicted in red. The database itself has far higher resolution than depicted in this example. The most precise data are observations just 30 meters by 30 meters, precise enough to detect buildings, driveways and swimming pools.

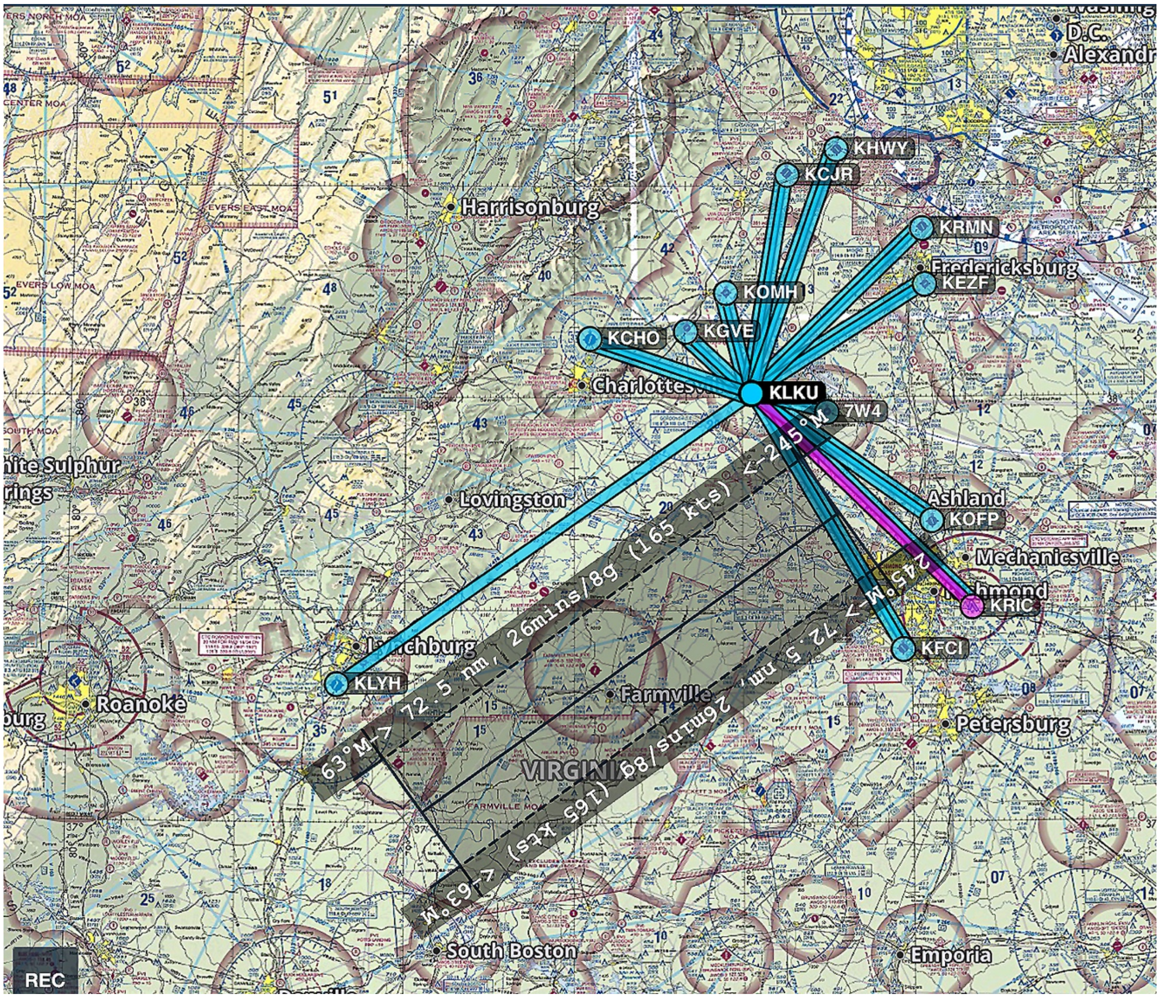
Appendix 4: Validation of Competitive Analysis Data Using Flight Planning Software

4a. Louisa County Airport in Virginia: Competitive Analysis of Airports in 50-mile Catchment Area



Using off-the-shelf flight planning software, a “flight” was planned from the focal airport to every airport computed to be in the airport’s catchment area (15-, 30- and 50-mile circles). In this example, the Louisa County Airport in Virginia has ten competitors within the 50-statute mile (43.5 nautical mile) catchment area.

4b. Louisa County Airport in Virginia: Competitive Analysis with an Airport Incorrectly Included



This image is identical to Appendix 4a, above, except with the intentional addition of an airport outside of the catchment area. The erroneous airport, Lynchburg (VA) is clearly erroneous and is about 72.5 nautical miles from Louisa County Airport, far outside the catchment area.

4c. Textual Analysis of Competitive Airports

4:12 AM Tue Feb 7 ••• 99%

KLKU to KLKU

Navlog
KLKU to KLKU

Route
KRIC KLKU KHWY KLKU 7W4 KLKU KCHO KLKU KCJR KLKU KRMN KLKU KEZF KLKU KOMH KLKU KOFP KLKU KFCI KLKU KGVE

WAYPOINT	AIRWAY	MAG HDG	MAG CRS	ALT	WIND CMP	WIND DIR/SPD	ISA	SPD KT TAS	SPD KT GS	DIST NM LEG	DIST NM REM	TIME LEG	TIME REM	ETE	ACT
KLKU		-	-	494	-	-	-6	0		-	6[illegible]9	-	3:48	-	
-TOC-	DCT	149	144	6000	T3	238/010	-6	110	1[illegible]3	15	6[illegible]4	0:07	3:41	0:07	
KRIC Richmond International	DCT	149	145	6000	T7	253/016	+1	165	1[illegible]2	28	5[illegible]6	0:10	3:31	0:17	
KLKU Louisa County/Freeman Field	DCT	322	325	6000	H8	267/012	+1	165	1[illegible]7	43	5[illegible]3	0:17	3:14	0:34	
KHWY Warrenton/Fauquier	DCT	025	029	6000	T10	252/017	+1	165	1[illegible]5	37	4[illegible]6	0:12	3:02	0:46	
KLKU Louisa County/Freeman Field	DCT	214	210	6000	H13	242/017	+2	165	1[illegible]2	37	4[illegible]9	0:15	2:47	1:01	
7W4 Lake Anna	DCT	117	114	6000	T15	254/018	+2	165	1[illegible]0	11	4[illegible]8	0:04	2:43	1:05	
KLKU Louisa County/Freeman Field	DCT	291	294	6000	H16	254/018	+2	165	1[illegible]9	11	4[illegible]7	0:04	2:39	1:09	
KCHO Charlottesville-Albemarle	DCT	296	299	6000	H15	255/018	+2	165	1[illegible]0	24	4[illegible]3	0:10	2:29	1:19	
KLKU Louisa County/Freeman Field	DCT	122	119	6000	T15	255/018	+2	165	1[illegible]0	24	3[illegible]9	0:08	2:21	1:27	
KCJR Culpeper Regional	DCT	014	020	6000	T6	256/018	+2	165	1[illegible]1	31	3[illegible]8	0:11	2:10	1:38	
KLKU Louisa County/Freeman Field	DCT	205	200	6000	H12	244/019	+2	165	1[illegible]3	32	3[illegible]6	0:12	1:58	1:50	
KRMN Stafford Regional	DCT	053	056	6000	T16	257/019	+2	165	1[illegible]1	33	2[illegible]3	0:11	1:47	2:01	
KLKU Louisa County/Freeman Field	DCT	240	237	6000	H12	262/015	+1	165	1[illegible]3	34	2[illegible]9	0:13	1:34	2:14	
KEZF Shannon	DCT	065	068	6000	T18	259/019	+2	165	1[illegible]3	29	2[illegible]0	0:10	1:24	2:24	
KLKU Louisa County/Freeman Field	DCT	251	249	6000	H14	260/015	+1	165	1[illegible]1	29	2[illegible]1	0:11	1:13	2:35	
KOMH Orange County	DCT	349	356	6000	H3	260/020	+2	165	1[illegible]2	15	1[illegible]6	0:06	1:07	2:41	
KLKU Louisa County/Freeman Field	DCT	183	176	6000	H0	260/020	+2	165	1[illegible]5	14	1[illegible]2	0:05	1:02	2:46	
KOFP Hanover County Municipal	DCT	140	135	6000	T13	260/020	+2	165	1[illegible]8	32	1[illegible]0	0:11	0:51	2:57	
KLKU Louisa County/Freeman Field	DCT	312	316	6000	H11	258/016	+1	165	1[illegible]4	31	1[illegible]9	0:12	0:39	3:09	

This is a screenshot from the flight planning software and shows the distance in nautical miles from the focal airport (Louisa County Airport, LKU) to each airport in the catchment area. The distances inside the red box are the length of each "leg" of the flight (displayed in nautical miles) back and forth to LKU. No distances were greater than 43.5 nautical miles so all of those airports are within the 50 statute mile catchment area.

Appendix 5: Examples of Isolated Airports with Impaired Access

These two images are exemplars of isolated airports where it is difficult to generate significant economic impact. The Marathon Airport has only 12.2 square miles of land and 11,019 people in the 15-mile catchment area. Nonetheless, it produces an economic impact of $106,239,000, ranking it #72 of the 235 airports in the study. In contrast, Wakulla Airport, on the Florida panhandle, ranks #235 in the study. It has 359.7 sq. miles of land at 17,155 people in the 15-mile zone, but with only one road to the airport access is impaired and economic development is challenging.

BIOGRAPHICAL SKETCH

Mike Jones is a businessperson, a veteran, a pilot, a writer, and an advocate for anything with wings. His business career involved a decade in marketing with AT&T. He then switched to a start-up company specializing in the chemistries and processes involved in critical cleaning applications. During his four decades with that firm the company grew to more than 130 employees and opened offices in Europe, the UK and Singapore. He has worked in more than 60 countries, published more than 40 technical articles on critical cleaning technologies and has presented at industrial conferences on four continents.

More recently, Jones has served for eight years on the Pinehurst (NC) Airport Authority, working for eighteen months as chairman of that body. He's been a commercially-rated pilot for thirty years and flies his red and white Cessna to airshows and fly-in events. He also is a well-known aviation writer with feature articles published monthly in "Cessna Pilots Magazine." Mr. Jones lives in Southern Pines, is married, and when not working on airport issues enjoys gardening, cooking and golf. He is a graduate of Columbia University (M.B.A., 1976) and Grove City (PA) College (B.A., 1973), and served as an air traffic controller in the U.S. Air Force at the close of the Vietnam War.