

Efficiency Studies of the US Transportation Sector

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ABSTRACT

Transportation builds the economy by moving people and goods. The transportation systems and their networks are growing very rapidly to smoothen the overall traffic flow. It also has resulted in increased energy use, traffic congestion, pollutions, and land-use change. US airports play an important role in the nation's economic growth. The deregulation process of US aviation in 1978 has led airlines and airports to be more dynamic and competitive through economies of scale and rapid adaption to technological changes. However, in recent years, many airports lack dedicated infrastructure investment. They are experiencing outdated facilities and crowded terminals. They are operating beyond their capacity. Furthermore, there are negative externalities such as, flight delays, pollutions generated because of the operation of US airports. The U.S. freight sector also has continued to expand over the past decades and made a key role in linking the nation's economic activities. In 2018, nearly 5.3 trillion ton-miles of goods were moved in the nation with trucks as the dominant mode. The increase of road freight transport presumably maintains given the surging development of eCommerce and easiness of online shopping. Such growth in the freight demand likely increase the fuel used in the road freight and result in more greenhouse gas (GHG) emissions.

Therefore, it is important to make sure the system is efficient to reduce energy use and related pollutions, and to save congestion/delay time, and operating costs. Therefore, efficiency analysis in transportation problems has gained considerable research attention in the past two decades. The overall aim of this study is to determine the efficiency of two major transportation services, airports, and road freight, in the United States.

The operational efficiency of the 50 US airports in 2009-2018 is analyzed by considering local air pollutions and flight delays as undesirable outputs, and related carryover activities (such as debt, expenditure, and use capital) to account for the linkage of consecutive periods. Further investigation examines the factors that could explain the variation among airport efficiency. The results indicate that it is crucial to include carryovers and undesirable outputs into consideration when analyzing the efficiency of airports. We found that medium airports perform better with the undesirable outputs/ carryovers' inclusion. Some inefficient airports have improved their operations to reach the efficient frontier over time, while a smaller number remained inefficient given the years. We found that the efficiency of the US airports depends on the hub size, population density, GDP, international share of flights, fleet size, and local workforce.

We also analyze the rebound effect generated from the energy efficiency improvement in the US road freight transport including under asymmetric energy price responses. Our results suggest that the rebound effect exists in US road freight transport and that the effect has increased in recent years. We also found that the rebound effect increases with decreases in energy price and decreases with energy price increases. Important policy implications of the findings have been discussed.

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CHAPTER I

INTRODUCTION

Transportation is building the formation and development of civilizations and economies throughout history. It provides services for the goods and people. The transportation systems smoothen the overall traffic flow. However, the continuous development in transportations also has resulted in increased energy consumption, traffic, greenhouse gas emissions (GHG), and change in land use for transportation infrastructure (Mahmoudi et al., 2020). The transportation sector is one of the leading energy users that produces a lot of pollutions in the world (Fuglestedt et al., 2008). Therefore, with the rapid expansion of the transportation system, it is important to make sure the system is efficient to reduce energy use and related pollutions, and to save congestion/delay time, and operating costs. It is seen that improving the operational efficiency in transportation systems, costs can be reduced by 15-20% (4flow, 2017). Moreover, better information can help businesses to select more efficient points/locations to gain more businesses. It also guides the government to allocate resources for appropriate programs (Carlucci et al., 2018). Therefore, efficiency analysis in transportation problems has gained considerable research attention in the past two decades.

Airports play an important role globally in the economic growth by supplying transportation services for people and cargo. The deregulation process of US aviation in the later 1970s has led airlines and airports to be more dynamic and competitive through economies of scale and rapid adaption to technological changes (Pathomsiri et al., 2008). Thus, the US air transport industry contributes \$768.4 to national GDP in 2011-2013 (NAS,

2015). However, in recent years, many airports lack dedicated infrastructure investment. They are experiencing outdated facilities and crowded terminals. They are operating beyond their capacity (Burke, 2014). Furthermore, there are negative externalities such as, flight delays, pollutions generated as a result of the operation of US airports. These are becoming a major concern for passengers, airlines, and airport managers. It is estimated that 23% of flights were delayed in 2014 (BTS, 2020). Airports affect the air quality for nearby communities. The environmental protection agency (EPA) estimated that US airports contribute about 12% of US transportation emissions (2019). Raising concerns have a growing interest among researchers, practitioners, and policymakers to assess the strength of US airports by analyzing their efficiencies.

The US freight sector also plays a key role in the nation's economic growth. It has continued to expand over the past decades. In 2018, nearly 5.3 trillion ton-miles of goods were moved in the nation with trucks as the dominant mode (BTS, 2018a). The growth in road freight transport should continue given the surging development of eCommerce. Such growth in the freight demand will likely increase fuel use resulting in more GHG emissions. The US transport sector surpassed the electric power sector in 2016 to become the top source of national GHG emissions, producing 23 percent of US transport emissions (EPA, 2017; C2ES, 2013). To mitigate the upward trend of energy use and GHG emissions in road transportation, various policies have been introduced to improve fuel technology, decrease emissions, and reduce costs. Such improvements may initially lower freight fuel use and reduce emissions. However, cost savings from efficiency improvement may trigger more energy consumption in the freight sector thus offsetting the reductions in GHG. This

so-called rebound effect has been observed in the road freight sector in various countries, such as Canada and the European Union (EU) and could result in nonattainment of policy goals.

Two types of methods are being used for analyzing the efficiency of the transportation sector. One is the parametric methods, e.g., stochastic frontier analysis (SFA) that estimates efficiency using econometric techniques (Scotti et al., 2012). Another one is the non-parametric methods, e.g., data envelopment analysis (DEA) (Curi et al., 2011). In the last 10 years, more than 80% of the published papers in the air transportation systems are related to the use of DEA (Mahmoudi et al., 2020). Also, transportation is ranked 4th most common application to use DEA in the last three years (Emrouznejad & Yang, 2017). DEA measures the relative efficiency of the decision-making units (DMUs) from a set of inputs and outputs (Tone, 2001). Among various DEA efficiency models, slack-based measure (SBM) DEA is regarded acceptable means for constructing an efficient frontier identifying input excesses and output shortfalls (Amowine et al., 2019). Besides inputs and outputs, investments that extend to multiple periods can be modeled, i.e., in-progress expenditure, debt, capital, among others. Those carryovers need to be considered in the efficiency analysis, otherwise the dynamic mechanism in efficiency calculations will be overlooked (Tone & Tsutsui, 2010). Tone & Tsutsui (2010) introduced carryovers as a connection over time for efficiency calculation in the dynamic SBM DEA (DSBM DEA) model. A few studies used carryovers in the efficiency estimation., however, incorporating carryovers in the airport literature is still lacking. Hence, DSBM DEA is used to analyze the operational efficiency of 50 US airports. For the aggregate US road freight

sector, SBM DEA is used to generate the annual efficiency score to further estimate the associated rebound effect.

The overall goal of this thesis thus is to determine the efficiency of two major transportation services, airports and road freight, in the United States. Chapter 2 examines the operational efficiency of the US airports by considering local air pollutions and flight delays as undesirable outputs, and related carryover activities to account for the linkage of consecutive periods. It will further investigate the factors that can potentially explain the variation among the efficiency scores of the airports. Chapter 3 focuses on the rebound effect generated from the energy efficiency improvement in the US road freight transport. It further examines the rebound effect scenarios under asymmetric energy price responses. These analyses will assist the government and academia to further their understanding of the potentials for improving the efficiency of US transportation service and mitigating associated environmental impacts.

CHAPTER II
ESTIMATING THE OPERATIONAL EFFICIENCY OF THE US
AIRPORTS

I write my paper from the scratch. I use secondary data for my second paper. I collected secondary data from different sources including the FAA, Bureau of Labor Statistics, Bureau of Transportation Statistics, the World bank, etc. I also use a purchased database from APEX. After carefully reviewing the existing literature, I use one of the most popular methods to obtain my objectives. I also use a second-stage method to explain the first-stage results. Based on the analysis, I discuss the potential implications and try to give some recommendations.

Abstract

The deregulation process of US aviation in 1978 has led airlines and airports to be more dynamic and competitive through economies of scale and rapid adaption to technological changes. However, in recent years, many airports lack dedicated infrastructure investment. They are experiencing outdated facilities and crowded terminals. They are operating beyond their capacity. Furthermore, there are negative externalities such as, flight delays, pollutions generated because of the operation of US airports, which led researchers to use data envelopment analysis (DEA) model to assess airport's efficiency. However, introduction of carry-over activities as dynamic properties was particularly ignored in the previous modeling. This study provides a comprehensive performance evaluation of 50 US airports during 2009-2018 by using a two-stage analysis. In the first stage, the efficiency of the US airports is estimated by applying the dynamic slack-based DEA considering emissions and flight delays as undesirable outputs, and related carryovers. In the second-stage analysis, a truncated bootstrapped regression is applied to investigate the factors that can explain the variation among the first stage efficiency scores. The results indicate that it is crucial to include carryovers and undesirable outputs into consideration when analyzing the efficiency of airports. It shows a positive correlation between airport's traffic and the carryovers/ undesirable outputs. We found that the efficiency of the US airports depends on the hub size, population density, GDP, international share of flights, fleet size, and local workforce. Important policy implications of the findings have been discussed.

Keywords: US airports, operational efficiency, data envelopment analysis, dynamic, carryovers, undesirable outputs

Introduction

Airports play an important role in a country's economic growth by providing air transportation services for people and cargo. Airports also smooth the supply chain flows by linking various modes of transportation (Ahn & Min, 2014). According to Air Transport Action Group (ATAG) (2020), the aviation industry transports around two billion passengers annually, and 40% of exports of goods. It generates almost 29 million jobs globally. The aviation industry has an estimated global economic impact of \$2960 billion, which is equivalent to 8% of world gross domestic product (GDP) (ATAG, 2020). It is a net contributor to national treasuries (Mott MacDonald, 2008). The US aviation industry generated 768.4 billion in GDP in 2011-2013 (NASEM, 2015).

The deregulation of US aviation industry in 1978 has led airlines and airports to become more competitive through economies of scale, reduction in duplicated services, and rapid adaption to technological changes (Pathomsiri et al., 2008). Airports have improved their capital expenditures and efficiency of capital use in the 80's and 90's. However, over the past decade, the infrastructure investment and management of US aviation industry has not been able to meet the surging air travels (Burke, 2014). Many of airports are experiencing crowded terminals and outdated facilities as they are operating beyond their capacity. Thus, the efficiency of US airports has received increasing attention from governments, academia, and the general public.

When evaluating airports' efficiency, the data envelopment analysis (DEA) has been widely used because of its simplicity of forming efficient frontier to identify efficient airports given a set of inputs, desirable outputs, and sometimes undesirable outputs (Gillen

& Lall, 1997). Among various DEA models, the slack-based measure (SBM) DEA model developed by Tone (2001) has been increasingly adopted given its ability to construct an efficient frontier identifying input excesses and output shortfalls (Amowine et al., 2019). Hence, it has a superior power in the environmental decision-making units (DMUs) estimation. Furthermore, the SBM is a non-radial model. It can deal with inputs/outputs individually, whereas the radial DEA models assume proportional changes in inputs/outputs (Tone & Tsutsui, 2011).

Some investments in airport infrastructure extend to multiple periods, such as debt, in-progress investment, capital, among others. Such carry-over activities need to be considered in the evaluation of airports efficiency to generate more legitimate estimates (Tone & Tsutsui, 2010). To estimate the overall and periodic efficiencies, Tone & Tsutsui (2010) developed a dynamic SBM DEA (DSBM DEA) model by integrating the carry-overs as linking variables between two consecutive periods, which helps to generate more accurate efficiency scores than traditional static models (Lu et al., 2019). Guo et al. (2017) used capital stock as carry-over in their DSBM DEA model to evaluate energy efficiency of the organization for economic co-operation and development (OECD) countries and China. A growing number of studies have taken into account of carry-over activities in their efficiency analysis for the energy and water sectors (Amowine et al., 2019; Li et al., 2018). However, incorporating carry-over activities in the efficiency analysis is still lacking in the airport literature.

To further enhance the efficiency analysis of airports, the undesirable outputs from airport operations need to be considered as the adverse social impacts are the major concerns for the passengers, airlines, and managers (Pathomsiri et al., 2008). Flight delay

is considered as one of the undesirable outputs of airport operations. In 2014, it is estimated around 23% of flights of all the US airports delayed (BTS, 2020). Flight delay has a serious strain on the US air travel system that costs airlines, passengers, and the society. Avoiding air travel by passengers due to flight delays incurs a significant welfare loss to the airlines and airports (NEXTOR, 2010). Therefore, the level of delays is suggested to be included in the airport performance evaluation because a congested airport might appear to be efficient given its high level of air-traffic or aeronautical revenue (Pathomsiri et al., 2008). Also, air pollution is one of the negative products of airport operation. EPA estimated that aircraft contribute around 12% of US transportation emissions (EPA, 2019). As assessing local air quality is relevant for both the people around airports and airport managers, it should be considered in the efficiency estimation (Gao, 2000).

It would be important to understand what factors may potentially affect the efficiency. Thus, a second stage analysis that regresses the DEA scores on the potential influential factors could help researchers and policymakers address the challenges of efficiency improvement. It is seen from the previous studies that hub status of the airport, population around the airport, regional GDP, percentage of international flights, etc. can explain the variation of efficiency among airports (Chu et al., 2010; Parelman & Serebrisky, 2010; Tsui et al., 2014a; Oum et al., 2006; Scotti et al., 2014; Barros & Sampaio, 2004).

The aforementioned studies have enhanced our knowledge of airport efficiency estimation. However, incorporating both carry-over activities/factors and undesirable outputs in the evaluation of airport efficiency is still lacking. Therefore, given the

increasing concern regarding the efficiency of US airports, this study aims to determine the relative efficiency of 50 US major airports during 2009-2018 using a recently developed two-stage dynamic DEA model. In stage one, the relative efficiency of the US airports is estimated using the DSBM DEA model incorporating carryovers and undesirable outputs. In two stage, a truncated bootstrapped regression is applied to investigate the factors that potentially explain the variation among the airports' efficiency scores.

Literature Review

The analysis of airport efficiency has become imperative because of their increased economic and strategic importance (Sarkis and Talluri, 2004). Airport globalization and increased competition have generated business pressures on operating firms. Thus, the information regarding efficiency helps airline companies select more efficient airports to gain more businesses, and guides governments to allocate resources for airport improvement programs (Carlucci et al., 2018). Hence, estimating the airport efficiency has captured some growing interests among researchers, practitioners, and policymakers. The methods used for analyzing the efficiency are classified into two categories. One applies parametric method, e.g. stochastic frontier analysis (SFA), to estimate efficiency using econometric techniques (Scotti et al., 2012), while the other one utilizes the non-parametric approach, e.g., data envelopment analysis (DEA). DEA measures the relative efficiency of the decision-making units (DMUs) from a set of inputs and outputs. DEA has become increasingly popular in the analysis of various research problems, especially transportation problems, over the last two decades. In the last 10 years, more than 80% of the published papers in the air transportation systems are related to the use of DEA (Mahmoudi et al.,

2020). A considerable number of studies are done on airport operations efficiency using DEA. Prior literature used different combinations of inputs and outputs variables to estimate airport efficiency. Those analyses were done with operational/physical variables, financial variables, or a mix of financial and operational variables e.g., airport area, number of gates, runways, operating cost, revenues, among others (Marques & Simoes, 2006; Fung et al., 2008).

A number of studies on airport efficiency that were conducted on the basis of physical variables are summarized in Table 1 *[insert Table 1 here]*. Suzuki et al. (2010) estimated the efficiency of 30 European airports based on physical parameters with a Slack-Based Measure (SBM) DEA model, where the number of runways, gates, employees, and airport area are considered as input variables, with enplanements, cargo, and aircrafts' landings and take-offs (LTOs) are used as outputs variables. Marques & Simoes (2006), Fung et al. (2008), Ha et al. (2010), and Orkcu et al. (2016) used similar inputs and outputs in their DEA efficiency analysis. Tsekeris (2011) used additional operating hours in evaluating the relative technical efficiency of Greek airports. Lozano & Gutierrez (2011) estimated the efficiency of 39 Spanish airports with an SBM DEA model with the goal of increasing aircraft movements with existing infrastructure. They included the number of baggage belts, apron size, check-in counters as input variables along with runways, gates, and employees in their study. Curi et al., 2011, Yu, 2010, Wanke, 2012 also included apron size, and the number of aircraft parking spaces as inputs. The exact reasons why DEA studies employ physical variables without considering the financial variables are, however, complex. One of the reasons might be the lack of available or difficulty in obtaining financial data for each airport (Tsui, 2014a).

Airports currently operate as commercial organization with the goal of maximizing profit based on aeronautical and non-aeronautical revenue streams (Graham, 2008). Thus, several prior DEA studies used financial indicators as inputs and outputs in estimating airport efficiency. Table 2 shows a summary of previous studies on airport efficiency with a mixture of financial and other variables *[insert Table 2 here]*. For the financial DEA models, labor cost, materials cost, capital cost, and other investment costs are considered as input variables, whereas aeronautical and non-aeronautical revenues are used as outputs (Carlucci et al., 2018; Barros & Dieke, 2007; Zou et al., 2015; Lai et al., 2015; Nicola et al., 2013; Sarkis & Talluri, 2004).

Over the past decade, undesirable outputs, such as air pollutants or delays, have been included in the analyses of airports efficiency and are of course minimized in the model specification (Gomes & Lins, 2017). According to Dyckhoff & Allen (2001), one way to deal with the undesirable output is to consider DEA as a multi-criteria approach where undesirable output is modeled as input. Based on Scheel (2001), a typical production possibility set can be created by using the reciprocal additive transformation (i.e., $f(U) = -U$) (i.e, treat the negative of undesirable output as a desirable outcome). Martini et al. (2011) used local air pollution as an undesirable output estimating the efficiency of 33 Italian airports. Lozano & Gutierrez (2011) used flight delays as an undesirable output assessing the efficiency of 39 Spanish airports with a SBM DEA model. Nicola et al. (2013) also used flight delays & the percentage of mishandled bags as undesirable outputs in their modeling of airport efficiency. Moreover, Scotti et al. (2014) included local air pollution, noise, & flight delays as undesirable outputs in their model to

estimate the efficiency of 44 US airports. They showed that when undesirable outputs are included in the airport models, the average efficiency increases and the efficiency gaps among airports decreases. This claim was also demonstrated by Yu (2004), Yu et al. (2008), Pathomsiri et al. (2008), and Lozano & Gutierrez (2010).

The SBM DEA model has a higher discriminatory power than the traditional DEA models (Zhou et al., 2008). However, these models are static, which assumes that production technologies are independent over time. Hence, changes in intertemporal efficiency can be overlooked, which has always been a concern in DEA efficiency-based estimations (Tone & Tsutsui, 2010). Capturing the dynamic characteristics in efficiency calculation is important, as this aspect allows the researchers to understand the efficiency changing mechanism of an entity over time. The Malmquist index and window analysis are some of the representative methods. The former is proposed by Fare et al. (1994) while the latter one is proposed by Klopp (1985) to analyze efficiency change between two periods. However, the carry-over activities over consecutive periods are not considered in either method because both have inputs and outputs denoted by time period, but neither account for the connection between time periods (thus ignoring carry-over impacts across time and thereby possibly overestimating the efficiency of the system being modeled) (Guo et al., 2017; Lu et al., 2019). Accordingly, it is important to use a dynamic framework in efficiency calculation.

Fare and Grosskopf (1996) first proposed the dynamic DEA model for formally dealing with the inter-connecting activities. However, Tone and Tsutsui (2010) extended the dynamic models into a slack-based measure by using carry-over activities as a

connection over time. Weights can be assigned to input/output items according to their importance. Furthermore, the carry-overs can be categorized into four kinds, called links, which reflect the actual characteristics of carry-over activities, are described as follows:

- **Desirable (good) link (CG):** It is the desirable carry-over to be carried forward. For example, net earned surplus (profit) can be carried to the next term. In the dynamic SBM (DSBM), desirable links are treated as outputs and link value is restricted to be not less than the observed one (Tone and Tsutsui, 2010).
- **Undesirable (bad) link (CB):** This is undesirable carry-over like loss carried forward, bad debt, and dead stock. Undesirable links are treated as inputs and its value is restricted to be not greater than the observed one in the DSBM (Tone and Tsutsui, 2010).
- **Discretionary (free) link (CF):** This is a carry-over that DMU can handle freely. Its value can be increased or decreased from the observed one. The deviation from the current value is not directly reflected in the efficiency evaluation, but the continuity condition between the two terms explained in the next section exerts an indirect effect on the efficiency score (Tone and Tsutsui, 2010).
- **Non-discretionary (fixed) link (CN):** This is the carry-over that is beyond the control of DMU. Its value is fixed at the observed level. Like the free link, fixed link affects the efficiency score indirectly through the continuity condition between two terms (Tone and Tsutsui, 2010).

Inclusion of carryover activities in the dynamic DEA model improves the estimation by considering the temporal relationship. Yeh et al. (2016) incorporated

organizational learning as carry-over to their dynamic SBM (DSBM) DEA model to find the impact of organizational learning on the dynamic recycling performance of Taiwan's 23 municipal solid waste system. Guo et al. (2017) used energy stock as carry-over in their DSBM DEA model to evaluate the energy efficiency of China & OECD countries. Amowine et al. (2019) used GDP as carry-over in the DSBM DEA model to assess aggregate energy efficiency improvement in 25 African countries. Li et al. (2018) employed assets as carry-over in the DSBM DEA model to estimate energy and air quality index performance of 31 cities of China.

In the US airports' perspective, the impact of airport capital improvement program on airport efficiency has also been evaluated in the literature. The primary source of airport capital improvement funding comes from passenger facility charge (PFC) (Burke, 2014). Airport Improvement Program (AIP) is another fund to improve airport capital planning and development. Based on these funds, a few researchers tried to analyze the performance of US airports. Zou et al. (2015) found that increasing AIP degrades airport performance whereas increasing PFC improves it. However, previous research has not considered the dynamics of those funds for investing in the infrastructure development, capital improvement, and existing resources on the performance evaluation of the airports. The carry-over in-progress expenditure and debt was ignored in previous research. Moreover, to our best knowledge, inclusion of both carry-overs and undesirable outputs to evaluate airport's efficiency is still lacking in the literature.

Though DEA models are capable of evaluating the airport efficiency using physical and/or financial variables in the analysis, there remains uncertainty regarding which factors

cause efficiency to vary (Gillen & Lall, 1997). A clear understanding of the determinants affecting airport efficiency would help policymakers and airport managers improve performance. A combination of second-stage analysis and first-stage DEA analysis (Tsui et al., 2014b) can be used to shed light on key determinants of efficiency. In the second stage, the DEA efficiency obtained in the first stage is regressed on the determinants to airport efficiency. A considerable number of second-stage studies are done to investigate the airport efficiency that are shown in Table 3 *[insert Table 3 here]*. It is seen that a range of variables are used for the second-stage analysis. Airport hub status, regional population, regional GDP, market share, percentage of low-cost carriers, workload unit, ownership, passenger per runway, cargo handled per runway, airport fleet size, percentage of international flights, etc. are all variables that have been used for the second-stage analysis (Merket & Mangia, 2014; Barros & Sampaio, 2004; Barros, 2008; Chu et al., 2010; Curi et al., 2010; Gitto et al., 2010; Parelman & Serebrisky, 2010; Ha et al., 2013; Tsui et al., 2014a, 2014b; Millan et al., 2016; Recupero, 2017; Nwaogbe et al., 2018; Scotti et al., 2014; Ngo et al., 2020).

While Tobit regression is the modeling approach in some papers (Barros & Sampaio, 2004; Chu et al., 2010; Ha et al., 2013; Merket & Mangia, 2014, Millan et al., 2016), others (Curi et al., 2010; Parelman and Serebrisky, 2010) have used truncated regression (Table 3). However, such approaches can have misled results because efficiency estimates generated from the first stage can be interdependent (Xue and Harker, 1999; Casu and Molyneux, 2003), thus violating a basic assumption of regression analysis. Accordingly, Simar & Wilson (2007) introduced a bootstrapping approach to deal with this

problem. In their approach, bootstrap samples are repeatedly created by randomly selected observations from the original data. The same regression model is performed to each sample to obtain the bootstrap estimates (Simar & Wilson, 2007).

Merkert & Assaf (2015) used the truncated bootstrapped regression to estimate the efficiency and identify the potential factors of 30 international major airports in 2013. They found that bootstrapped regression can better explain and deliver powerful insights into the airports' performance. Similarly, a few other studies have adopted the bootstrapping approach in the second-stage analysis to enhance the evaluation of airport performance (Barros & Dieke, 2008; Orkcü et al., 2016; Tsui et al., 2014a; and Merkert & Mangia, 2012).

Method

First Stage DEA Modeling:

This study follows the methodology developed by Tone and Tsutsui (2010). Figure 1 explains the dynamic structure with carry-over activities *[insert Figure 1 here]*. Suppose there are n decision making units (DMUs) over T terms; each DMU has its inputs and outputs during the period t , then carry over (link) to the next period $(t + 1)$. It is also assumed to have a balanced panel data through terms 1 to T .

For the modeling, we use an input oriented dynamic SBM DEA model with variable returns to scale (VRS). Assuming there are n DMUs over T terms and Each DMU has m inputs.

P = non-discretionary (fixed) inputs ($i = 1, \dots, p$)

S = outputs ($i = 1, \dots, s$)

r = non-discretionary (fixed) outputs ($i = 1, \dots, r$)

z = link (carry over) has good, bad, free and fix four categories

w = term weight

The input oriented overall efficiency for DMU o (θ_o^*) is defined by equation (1),

$$\theta_o^* = \min \frac{1}{T} \sum_{t=1}^T w^t \left[1 - \frac{1}{m+nbad} \left(\sum_{i=1}^m \frac{w_i^- s_{it}^-}{x_{iot}} + \sum_{i=1}^{nbad} \frac{s_{it}^{bad}}{z_{iot}^{bad}} \right) \right] \quad (1)$$

This objective function deals with not only excesses in input resources, but also undesirable (bad) links as main targets of evaluation. Where, w^t and w_i^- are weights to term t and input i . These are exogenously supplied according to their importance and satisfy the conditions in equation (2),

$$\sum_{t=1}^T w^t = T \quad \text{and} \quad \sum_{i=1}^m w_i^- = m \quad (2)$$

We also can define the term efficiency θ_{ot}^* by the equation (3),

$$\theta_{ot}^* = 1 - \frac{1}{m+nbad} \left(\sum_{i=1}^m \frac{w_i^- s_{it}^-}{x_{iot}} + \sum_{i=1}^{nbad} \frac{s_{it}^{bad}}{z_{iot}^{bad}} \right) \quad (3)$$

The continuity of link flows (carry-overs) between terms t and $t + 1$ can be guaranteed by the following equation (4):

$$\sum_{j=1}^n z_{ijt}^\alpha \lambda_j^t = \sum_{j=1}^n z_{ijt}^\alpha \lambda_j^{t+1}, \quad (\forall i; t = 1, \dots, T - 1) \quad (4)$$

where the symbol α stands for good, bad, free or fix carry-over links. This constraint is critical for the dynamic model since it connects term t and term $t + 1$ activities. Using these expressions for production, we can express DMU $_o$ ($o = 1, \dots, n$) by the following equations (5-13):

$$x_{iot} = \sum_{j=1}^n x_{ijt} \lambda_j^t + s_{it}^- \quad (5)$$

$$x_{iot}^{fix} = \sum_{j=1}^n x_{ijt}^{fix} \lambda_j^t \quad (6)$$

$$y_{iot} = \sum_{j=1}^n y_{ijt} \lambda_j^t - s_{it}^- \quad (7)$$

$$y_{iot}^{fix} = \sum_{j=1}^n y_{ijt}^{fix} \lambda_j^t \quad (8)$$

$$z_{iot}^{good} = \sum_{j=1}^n z_{ijt}^{good} \lambda_j^t - s_{it}^{good} \quad (9)$$

$$z_{iot}^{bad} = \sum_{j=1}^n z_{ijt}^{bad} \lambda_j^t + s_{it}^{bad} \quad (10)$$

$$z_{iot}^{free} = \sum_{j=1}^n z_{ijt}^{free} \lambda_j^t + s_{it}^{free} \quad (11)$$

$$z_{iot}^{fix} = \sum_{j=1}^n z_{ijt}^{fix} \lambda_j^t \quad (12)$$

$$\sum_{j=1}^n \lambda_j^t = 1 \quad (13)$$

$$\lambda_j^t \geq 0, s_{it}^- \geq 0, s_{it}^+ \geq 0, s_{it}^{good} \geq 0, s_{it}^{bad} \geq 0, s_{it}^{fix} \geq 0, s_{it}^{free} : free (\forall i, t)$$

Here, s_{it}^- , s_{it}^+ , s_{it}^{good} , s_{it}^{bad} and s_{it}^{free} are slack variables denoting input excess, output shortfall, link shortfall, link excess and link deviation, respectively.

The first step in the productivity analysis of an airport lies in defining the airport production process, which is based on the activities for landside and airside areas. The landside area is open to the public, which includes public parking lots, public transportation, train stations, and access roads. In contrast, access to the airside area of an airport is tightly controlled. The airside area includes all areas accessible to aircraft, including runways, taxiways, and ramps. Airport efficiency models should focus on both

landside and airside activities of the airports (Gitto & Mancuso, 2012). The physical model examines the core airside facilities to assess airport management efficiency with respect to airport operations, whereas the financial model examines the monetary aspects of airside and landside business activities regarding management's exploitation of aeronautical and non-aeronautical revenues. Therefore, we analyze the airport operation in terms of both physical and financial perspectives.

To present the potential differences between the conventional DEA method and the approach used in this analysis, we first evaluate airport efficiency without considering the carry-over activities and undesirable outputs, referred as the base model (model 1). Then, we run three additional model with the inclusion of undesirable outputs and carryovers. Overall, the four models, comprised of financial and physical variables, are used to analyze the impacts of carry-overs and undesirable outputs on the airport operational efficiency. Each model has the same sets of inputs and outputs but differing combinations of undesirable outputs and carry-over activities.

Financial Modeling:

- Base model: This is the base financial model with no carry-overs and undesirable outputs
 - Set of inputs = {Labor cost, Material cost, Utilities cost}
 - Set of outputs = {Aeronautical Revenue, Non-aeronautical Revenue}
- Model 2: This model adds carry-overs links including in-progress expenditure and total debt to the base model. The difference in efficiency scores of base model and model 2 assesses the impacts of carry-over activities on the efficiency of airports.

- Model 3: This model adds undesirable outputs including flight delays and air pollutants to the base model. It will assess the impact of undesirable outputs on the efficiency of airports.
- Model 4: This model is the full financial model. It includes both carry-overs and undesirable outputs to the base model. The difference between the base model and model 4 will determine the impacts of carry-overs and undesirable outputs together on airport efficiency.

Following the literature, we choose two undesirable outputs including flight delays and air pollutants (Lozano and Gutierrez, 2011; Martini et al., 2011; Scotti et al., 2014). The delays include the delay from runway closure or configuration changes, the presence of adverse weather, volume when an airport is in its optimum configuration, equipment failure or outage causing reduced capacity, and other conditions such as airshow, aircraft emergency, bomb threat, frequency interference, military operations, nonradar procedure, and other factors. Estimates of total flight delays are collected from the FAA's operations network (OPSNET) data reports (FAA, 2020b). In terms of the air pollution produced during aircraft landings and taking offs (LTOs) at the airport, we follow the approach discussed in the "International Civil Aviation Organization" (ICAO) air quality manual (ICAO, 2016) , that is limited to Hydrocarbons (HC), Carbon Monoxide (CO), and Nitrogen Oxides (NO_x) as pollution (CO₂ is ignored because it does not directly affect local air quality while SO₂ emission and Particulate Matter (PM) are ignored because they are not part of the ICAO engine certification process.) According to the ICAO, a LTO is split into four phases as follows: take-off, climb (up to 3000 ft), approach (from 3000 ft to

landing), and idle (when aircraft is taxiing on the ground with engine-on) as shown in Figure 2 *[insert Figure 2 here]*. The reference values of the duration of each LTO phase are collected from ICAO-Annex 16 environmental protection volume II (ICAO, 2016). The values are reported in Table 4 *[insert Table 4 here]*.

To compute the emissions, we use several data sources. Total number LTOs for each engine type for each airport per year are purchased from the “APEX” database maintained by RDC aviation. Fuel flow per second and the emission quantity per kg fuel consumption for each engine type at each LTO cycle are collected from the ICAO aircraft engine databank (2019).

Following Martini et al. (2011), total emissions estimation can be formulated as following equation (14):

$$TE_{ip} = \sum_{c=1}^4 E_{ipc} * d_c * F_{ci} \quad (14)$$

Where, TE_{ip} is the total emissions of the LTO cycle for engine i and pollutant p, E_{ipc} is the emission factor of engine i of pollutant p for each LTO phase c, d_c is the duration of LTO phase c, and F_{ci} is the fuel consumption per second of engine i for the LTO phase c. By using the above equation, we estimate the HC, CO, & NOx emissions from each airport’s landing and take-offs operations. The summary statistics of these estimated emissions along with all the other variables used in our study are reported in Table 5 *[insert Table 5 here]*.

Physical Modeling:

Physical models are set up followed the same approach as financial models. The following variables are used to form all the cases for the physical models.

- Set of inputs = {Number of full-time employees}
- Set of outputs = {LTO, Enplanements, Cargo}
- Set of carry-overs = {Airport area, Number of Runways, Number of gates}
- Set of undesirable outputs = {HC emission, CO emission, NOx emission, Total flight delays.

Second-Stage Modeling:

To have a clear grasp on what factors affect the efficiency of an airport, we employ a second-stage approach. We use a truncated bootstrapped regression model for the second-stage analysis based on Simar and Wilson (2007). For this analysis, the efficiency scores obtained from the first-stage dynamic SBM DEA model are regressed on the specific operating characteristics of the airports, and airport's county demographic profile.

The truncated bootstrapped regression specification can be written as following equation (15),

$$\theta_{ot}^* = \alpha + \beta_{ot} * X_{ot} + \varepsilon_{ot} \quad (15)$$

Where, θ_{ot}^* is the t term efficiency of the o airport, α is the constant, β_{ot} is the coefficient of airport-specific and airport's county demographic variables X_{ot} , & ε_{ot} is the error term. To perform this analysis, “pldv” function for panel truncated regression of “plm” package, and “boot” package of “R” software are used. We include “vcovHC”

argument in the “pldv” function, which uses the variance-covariance matrix to warrant the robustness of the model (Croissant et al., 2020).

Data and Selection of Variables

First-Stage Variables Selection:

The selection of variables for any DEA model is important because a firm or an entity may utilize multiple inputs to generate its outputs. A lot of studies have been done on airport efficiency. Based on prior numerous studies of airport efficiency (in terms of physical and financial aspects) and data availability we use labor cost (employee compensation), materials cost, & utilities costs as financial inputs. Employee compensation includes salaries and wages and benefit package costs (employee pensions, life insurance, and health insurance) for personnel employed directly by the airport. Utilities costs account for the cost of utilities and communication services used while operating the airport including telephone, electricity, water, heating, and air conditioning. Materials cost include the cost of other supplies and materials considered necessary to operate the airport. Aeronautical and non-aeronautical revenue are the outputs for the financial models. Aeronautical revenue includes all revenues derived from passenger airline, landing fees, terminal fees, federal inspections fees, security reimbursement from the federal government, fixed base operations, fuel sales profit, and other non-passenger airline fees. Non-aeronautical revenue includes revenues from land and non-terminal facility, food and beverage, retail stores, rental cars, parking & ground transportation, hotel, and other terminal services.

For financial models, we also use two carry-overs variables, in-progress capital expenditures and construction (IPE) and total debt, to account for the financial continuity

between two consecutive periods. IPE is a free carry-over (CF), as it is a positive approach to develop the airport infrastructure. It exerts an indirect effect on the efficiency score by connecting two consecutive terms. IPE includes in progress costs on airfield, terminal, parking facility, roadways, rail & transit developments. Total debt is a bad carry-over (CB), as it is the bad debt carried to the next term. It includes indebtedness at end of the year on long term bonds, loans and interim financing, and special facility bonds.

Input for physical models include the number of full-time employees at the end of each fiscal year (FTE), and total annual enplanements, total annual cargo load (in pounds), and total annual number of landing & take-offs (LTOs) (both passenger and cargo planes). Airport area, number of runways, and number of checking gates are considered carry-overs for physical models. The latter two are considered free carry-overs (CF), whereas the airport area is a fixed carry-over (CN).

A list of 30 large hub and 20 medium hub airports are selected for our study, which are shown in Table 6 *[insert Table 6 here]*. Our data covers a total of 10 years from 2009 to 2018. In total, we have 500 observations. Data are collected from several sources. Labor, materials, utility costs, aeronautical revenue, non-aeronautical revenue, IPE, total debt, enplanements, cargo, LTO, & FTE are collected from FAA-5100-127 form (FAA, 2020a). Airport area, number of runways, and the number of checking gates are collected from the airport master record AIRPORTQ-5010 (AirportQ, 2020).

Second-Stage Variables Selection:

For the second-stage panel truncated bootstrapped regression, we adopt six explanatory variables by following the previous literature. The aim is to determine the factors, which

may explain the variation in airport efficiency. Each of the explanatory variables is described below:

- *GDP*: Gross domestic product (GDP) is a potential factor that may play a role in explaining airport performance. It represents the socioeconomic environment in which the airport operates (Chu et al., 2010; Parelman & Serebrisky, 2010; Ha et al., 2013; Tsui et al., 2014a; Ngo et al., 2020). We incorporate all industry GDP of the county in which an airport is located. GDP is measured in billions of current US dollars. The data is collected from the Bureau of Economic Analysis (BEA, 2020). We anticipate that increase in airport county's GDP should have a positive impact on airport's performance.
- *Population Density*: To represent the market size served by an airport, the population of the county/city where the airport is located has been widely used (Barros & Sampaio, 2004; Parelman & Serebrisky, 2010; Merket & Mangia, 2014; Tsui et al., 2014b; Orkcu et al., 2016). However, the presence of both medium and large airports in the study sample may signify the local population density (Carlucci et al., 2018). Hence, a larger served population per unit of an area may have a positive impact on the airport's efficiency. Also, it may affect the efficiency negatively if the airport experiences capacity shortage to serve the large population. We use the population density of the county where the airport is located. The data represents the number of people (in thousands) per square mile of the airport county, which is generated from the BEA (2020) and the US Census Bureau (2011) data.

- *Percentage of acquiring a college degree:* Having a skilled labor force should enhance airport efficiency. We use the percentage of adults age 25-44 with some post-secondary education as a proxy of the skilled workforce. We expect to have a positive impact on airport's efficiency. The data is collected from the county health national database (County Health Rankings & Roadmaps, 2020). However, the data is only available from 2010 to 2018. We use 2010's data as a proxy for 2009, as the change of the data is negligible between the two consecutive years.
- *Percentage of International Flights:* The percentage of international flights has been identified as affecting airport efficiency in the literature (Chow et al., 2009; Oum et al., 2006, 2008; Scotti et al., 2014). It may positively affect the airport's performance. The variable is generated from the "APEX" database.
- *Fleet Size:* The mix of aircraft fleet may play an important role in explaining variations among airport's efficiency (Scotti et al., 2014). Larger aircraft fleet may have a positive impact on airport's performance. The average number of seats per LTO can characterize the size of the aircraft fleet presents in an airport. We also generate this information from the "APEX" database.
- *Hub Category Dummy:* Airport hub is important in explaining the variation of airport efficiency. Hub status can capture the importance of flight connectivity and the strategic location of an airport (Barros & Sampaio, 2004). If the airport hub is designed as a large hub (based on size), it is 1, otherwise 0. Large hub has the potential to generate a positive impact on airport's performance, however, it may also affect the airport's performance negatively (Tsui, 2014b).

Empirical Results

First-Stage Results:

Table 7 shows the first-stage analysis results from our adopted financial and physical models *[insert Table 7 here]*. Base model efficiency score refers to a standard DEA model and assumes values between 0 and 1. The airport is on the efficiency frontier when the score is 1, otherwise inefficient. Other models (financial models 2-4, and physical models 2-4) obtained from the DSBM DEA models also fall between 0 and 1. Our results indicate that the number of efficient airports increases with the inclusion of carryovers and undesirable outputs in the model progressions, which is consistent with the previous work on airport efficiency. For instance, the financial base model identifies only 8 efficient airports overall. An additional 8 and 11 airports are on the efficient frontier for models 2, and 3, respectively, with the inclusion of carryovers and undesirable outputs to the base model. When both the carryovers and undesirable outputs are simultaneously added to the base model, the effect is amplified with the number of efficient airports increase to 30 (i.e., 60% of the study sample). Results from the physical models follow a similar pattern (Table 7). The complete results of the physical model can be found in the appendix.

The increase of efficient airports with the inclusion of carry-overs or undesirable variables (or both) is consistent with the previous findings (Scotti et al., 2014). The lower the efficiency of an airport with the base inputs-outputs, the greater the probability that it will improve in terms of efficiency when additional variables are added (Scotti et al., 2014). In our case, the majority of improved efficiency happens in the medium airports from base model to model 4. When considering carryovers in the estimates, inefficient airports that have relatively less aeronautical and non-aeronautical revenue also may have relatively

less in-progress expenditure and debt. Likewise, for undesirable outputs, inefficient airports that generate relatively few LTOs also may generate less air pollution.

Table 8 illustrates the yearly efficiency scores of the financial model 4 that simultaneously uses carryovers and undesirable outputs to the base model *[insert Table 8 & 9 here]*. Out of the 30 efficient airports, 17 are large hub airports and 13 are medium hub airports. Their overall efficiency score is 0.934, with an average score of 0.91 for large hubs, and 0.96 for medium hubs. Though the number of efficient large airports is higher, a few large airports are not efficient of the sample, which brings back the overall score lower than the medium hubs. In particular, certain large hubs, McCarran international (LAS), Reagan national (DCA), Philadelphia international (PHL), Detroit metropolitan (DTW), and Salt Lake City (SLC) airports are relatively inefficient in comparison to medium hub airports. The sources of inefficiency for these least performing large airports suggest that the input costs and debt are higher, and IPE is lower than their projected score for being on the efficient frontier. For instance, to be efficient, SLC airport needs to increase IPE by 113%, as well as to lower the average annual costs for labor, utilities, materials, and debt by 36%, 14%, 83%, and 1%, respectively. DCA, another least performing large airport, must lower the costs for labor, utilities, and materials, and debt by 33%, 10%, 62%, and 25%, respectively, also to increase IPE by 130% for being efficient *[insert Table 10 here]*. Increasing IPE for the least performing airports also suggests that the inefficient airports need to invest more to strengthen infrastructure i.e., airfield, terminal, parking facility, roadways, rail & transit in order to accommodate the airport traffic.

Efficient airports remain on the efficient frontier consistently over time. Some inefficient airports had a trend of improving operational efficiency. For example, in financial model 4, Logan international airport (BOS) has a score of 0.92 in 2009 but improved to 1 from 2010 to 2018. Port Columbus International (CMH), a medium hub airport, showed consistent improvement in efficiency over time. In contrast, some airports became more inefficient given the years. For instance, Seattle-Tacoma international airport (SEA) produces a score of 1 during 2009-2016, but its efficiency declined to 0.81 in 2018. Salt Lake City international airport (SLC), the worst performing airport in the sample, has an overall score of 0.47, and showed a decline in 2012 to 2014 but later improvements in 2015 to 2018 *[insert Figure 3 here]*. To better understand this variability of the efficiency scores, we examine the second-stage results.

Second-Stage Results:

The estimated results from the bootstrapped truncated regression analysis are presented in Table 11 *[insert Table 11 here]*. As expected, the county GDP variable is significant and positive. Hence, there is a positive relationship between GDP and airport efficiency. Moreover, airport traffic demand and county GDP are positively correlated. This finding is supported by Abed et al. (2001), and Tsui et al. (2014c). Specifically, a one \$billion increase in GDP would improve airport efficiency minimally (0.0001 units). The population density is reported as having a negative coefficient. It indicates that if the county where the airport is located has a larger population per square mile, its efficiency would be reduced by 0.007 units. It also implies that an airport serving a larger population area tends to operate less efficiently than that a smaller population area. It could explain why the

medium hub airports perform better than the large hub airports in the first-stage analysis. This negative coefficient can also suggest that larger airport needs to build infrastructure or increase capacity to accommodate the larger population to be served.

The percentage of acquiring college degree is statistically significant and positive, which further proves the previous discussion for population density. The percentage of acquiring college degree does imply that airport efficiency may depend on the skill level of its county-level workforce. If the college-going percentage of a county where an airport is located increases by 1%, the efficiency of that airport is expected to improve by 0.001 units. Airport apparently have the opportunity to hire more highly skilled workers positively influences efficiency.

Fleet size has a statistically significant positive coefficient with an impact of 0.002, which indicates that an increase in the number of seats per LTO improves airport's performance by 0.002 units. Our estimated fleet size coefficient is consistent with the coefficient found in Scotti et al. (2014). More specifically, it indicates that if an airport's fleet size is larger, it tends to be more efficient. It can be related to the economies of scale, as large aircraft fleet needs less infrastructure or resources to accommodate the same quantity of cargo and passengers relatively compared to the small airports with smaller fleets. Furthermore, if an airport generates the same output with the larger aircraft will produce less pollutions, as emission factors do not increase proportionally with the size of aircraft (ICAO aircraft engine emissions databank, 2019).

The percentage of international flights has a statistically significant positive coefficient. It is also consistent with results from Scotti et al. (2014) but inconsistent with other studies, i.e. Pathomsiri et al. (2006) and Tsui et al. (2014a). It implies that a 1%

increase in the percentage of international flights of an airport tends to increase efficiency by 0.005 units. International flight share requires greater resources to process international passengers. Thus, large hub airport can accommodate this option. However, some large hub airports do not have that improved infrastructure to accommodate the traffic. An example is Salt Lake City international (SLC) large hub airport, which falls to the bottom of the efficiency rank. A very good number of medium hub airports are efficient indicating they are more able to accommodate international passengers as compared to some large hub airports.

The hub category is also significant but negatively, which is consistent with the findings of Tsui et al. (2014b). They argue that an international hub airport is less likely to be more efficient than a regional hub airport if the international hub lacks size and location advantages for handling a large amount of traffic. Our hub coefficient suggests that if the airport is a large hub airport, its efficiency will be reduced by 0.105 units compared to the medium hub airport. That is why the number of efficient medium hub airports increases with the inclusion of additional variables to the base model, whereas some large hub airports rank at the bottom in relative efficiency.

Conclusion

In this paper, we employ a two-stage analysis for a comprehensive performance evaluation of US airports. We use a sample of 30 large hub and 20 medium hub airports covering the period 2009-2018. For the first stage, we use the dynamic SBM DEA model for assessing airport efficiency by including carry-over activities, and undesirable outputs. We estimate airport efficiency from both financial and physical perspectives. The undesirable outputs

are flight delays, and HC, CO, NO_x emissions. We use different combinations of carry-overs for physical and financial models. In-progress expenditure, and debt are used as carry-overs for financial models, whereas airport area, number of gates, number of runways are for physical models. In first stage, we analyze four models for each financial and physical modeling to know the impacts of carry-overs and undesirable outputs on airport's efficiency. In addition, we investigate the factors contributing to the variation of the first stage airport efficiency scores using a second stage analysis, based on a truncated bootstrapped regression model.

Our results indicate that it is crucial to include carryovers and undesirable outputs into consideration when analyzing the efficiency of airports. It shows a positive correlation between the airport's traffic and the carryovers/ undesirable outputs. As large airports produce more desirable operations as well as more carryovers and undesirable outputs, vice-versa for medium airports. We found that more medium airports become efficient when undesirable outputs and carryovers are considered. We also have observed the change in efficiency over time. Some inefficient airports improved their operations to reach the efficient frontier over a decade, while a few remained inefficient over the study period.

Results also suggest that the GDP of the county where an airport is located has a positive impact on airport efficiency. More developed area tends to attract more airport traffic. However, the population density of the county where the airport is located tends to lower airport efficiency. This result suggests the need for such airports to build infrastructure or increase capacity to accommodate a larger customer base. Furthermore, if the percentage of acquiring college degree of a county where an airport is located increases,

the airport efficiency also increases, implying a local skilled workforce enhances the performance of an airport. Also, when the percentage of international flights increases, airport efficiency also tends to increase. It is also seen from our analysis that fleet size positively affects the efficiency of airports, which indicates that the larger aircraft fleet brings for more airport operations and activity due to the economies of scale. Airport hub status is negatively correlated with airport efficiency.

Our findings provide airport managers, scholars, or the government an updated information regarding ways for improving airport efficiency. To improve the efficiency, airport management with the airline authority can work to increase the number of large aircraft by reducing the number of small aircraft, especially for international flights, then the average number of seats per LTO (fleet size) would be increased. This will increase the airport's passenger capacity. Nonetheless, large aircraft may also generate more pollutions than small aircraft. If airports can trade-off large aircraft for fewer operations, emissions would certainly be reduced, which would help to improve the overall airport efficiency. In addition, organizations like the international air transport association (IATA) should work with airport management, airlines, and aircraft manufacturers to advocate for the regular use of sustainable jet fuels in commercial flights, which is more effective to reduce emissions than the traditional petroleum-based fuels (NASEM, 2016; Yilmaz and Atmanli, 2017). Reduction in air pollutants can especially help large airports enhance their efficiency. Furthermore, large airports need to improve facilities and services to cope with the increased traffic. This may be achieved through a new government investment fund solely dedicated to airport improvement.

Airports managers could also pay serious attention to some managerial measures to improve airport efficiency. For example, they may outsource some operational functions and services to specialized firms for saving operating costs and make efforts to generate some non-aeronautical revenues (e.g. concession revenues) (Tsui et al., 2014a). Moreover, airport management can consider forming an airline strategic alliance or partnerships. This may improve airport efficiency by delivering the best customer services with broad flight networks and frequencies. For example, Delta, Air France, and Alitalia joint venture benefitted each firms by generating the pooling of revenue from things like code-sharing and the ability for one airline to sell seats on another, which thus, optimizes the operation of these airlines (MRH, 2014).

The ongoing COVID-19 is ravaging the world economy from the beginning of 2020. The aviation industry, airlines, and airports are the worst hit of this pandemic from the travel restrictions and slump in demand among travelers. Prior to COVID-19, more than 2.7 million people flew in and out of the US every day. The traffic has decreased by approximately 87% by June 2020 (ACI, 2020). COVID-19 has emptied airports, and shrunk air traffic down to mostly essential travelers. Thus, both aeronautical and non-aeronautical revenues declined exponentially. Given these scenarios, the urgency of improving airport efficiency is even higher these days. Though our study reflects the scenarios prior to this pandemic hit, we draw some possible implications suited for the current situation. However, maintaining efficient operations might be beyond challenging.

While the revenues are under pressure, the airports may reduce the operating costs by relocating terminals, allowing certain employees to work from home, and halting the

ongoing expenditure on infrastructure. Furthermore, airports may take advantage of emerging technologies for smooth operations with limited resources. For instance, they may deploy autonomous robots for cleaning and sanitizing the common areas, which would encourage travelers to travel with minimal contact. Airports may also use augmented reality to alleviate the bottleneck of passengers at check-in sites and the crowds at departure boards (Roberts, 2020). Moreover, to maintain the social distancing norms, airport operations need to be changed through more self-service areas like mobile scan check-in and contactless border control, upgraded smartphone apps to maximize the overall operational efficiency.

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Appendix A

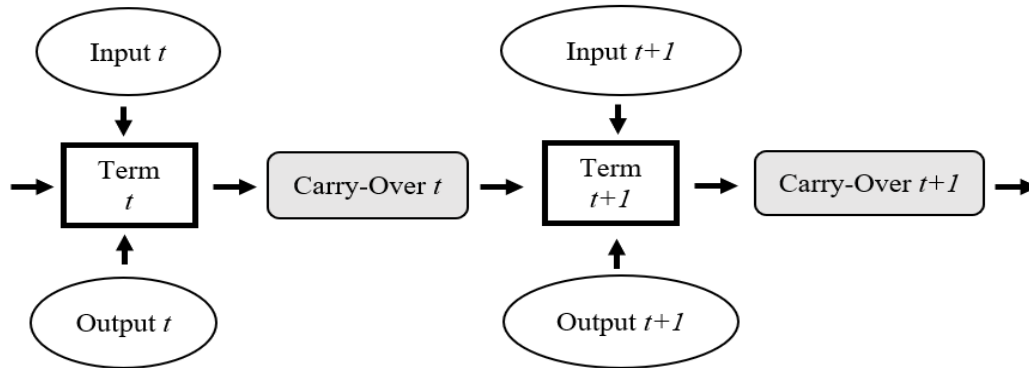


Figure 1: Dynamic Structure of SBM DEA (Tone and Tsutsui, 2010).

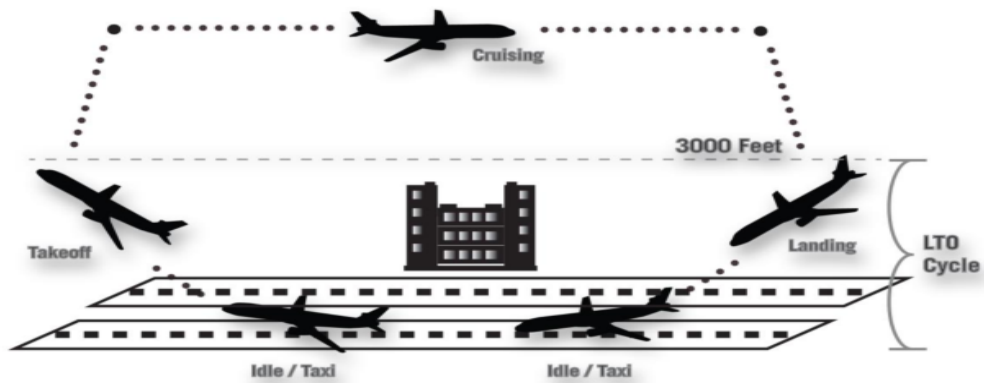


Figure 2: Schematic of the LTO cycle (Kim et al., 2009)

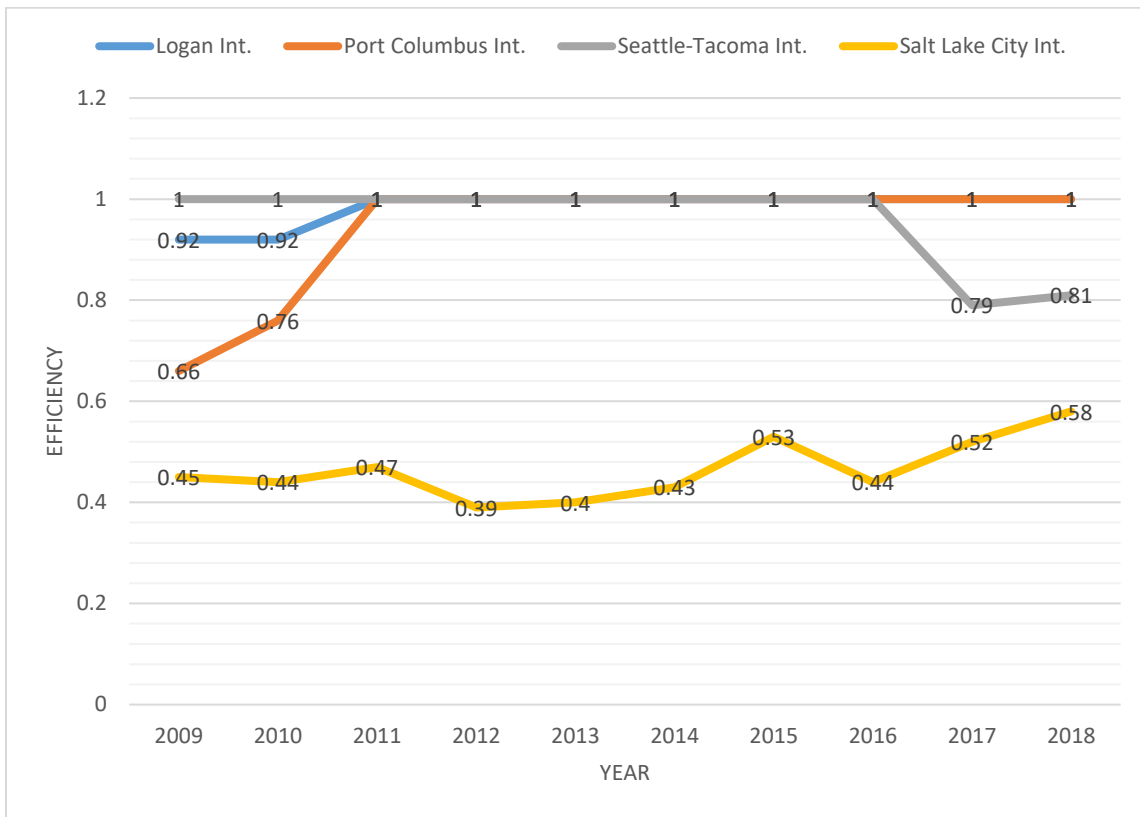


Figure 3: Efficiency Scores of Some Selected Airports Over Study Period of Financial Model 4

Table 1: Airport Efficiency based on Physical Parameters of the airports

Data Period	Title	Authors	Region	Objective	Input Variables	Output Variables	Undesirable output Variables
2007	Greek airports: efficiency measurement and analysis of determinants	Tsekeris T. (2011)	39 Greece Airports	Evaluating the performance of the Greek airports considering their relative technical efficiencies and factors determining these determinants.	Runways, terminal area, airplane parking area, operating hours	Passengers, cargo, landing and take-offs	NA
2006	Assessment of airport performance using the SBM-NDEA model	Yu MM (2010)	15 Taiwan Airports	Estimating airport's operations efficiency and the input excess and output shortfalls with respect to production and service process, respectively.	Employees, runways, apron, terminal	Passengers, cargo, landings and take-offs	NA
2005	A distance friction minimization approach in data envelopment analysis: a comparative study on airport efficiency	Suzuki et al. (2010)	30 European Airports	Aims at estimating airport efficiency by presenting a newly developed distance friction minimization model in the context of data envelopment analysis	Runways, terminal area, gates, employees	Passengers, landings and take-offs	NA
2006	Measuring the influence of congestion on efficiency in worldwide airports	Marques & Simoes (2010)	141 worldwide airports	evaluating the influence of congestion on the technical efficiency of airports using three different approaches.	Runways, gates, terminal area, employees	Landings and take-offs, passengers, cargo	NA
2007	Bootstrapped scale efficiency measures of UK airports	Assaf (2010)	27 UK Airports	Aims at analyzing and testing the scale efficiency of airports by using bootstrapping methods	Number of FTE, airport area, runways	Passengers, cargo, landings and take-offs	NA
2012	Airport efficiency in Pakistan - A Data Envelopment Analysis with weight restrictions	Ennen & Batoool (2018)	12 Pakistan Airports	Aims at estimating airport's efficiency by using predefined weight restrictions in the model	Number of runways, Terminal size, Number of employees	LTO, domestic passenger, international passenger, Cargo	NA
2000-2004	New evidence on the efficiency of Italian airports: A bootstrapped DEA analysis	Curi et al. (2011)	18 Italian airports	aims to measure the efficiency of Italian airports from the operational perspective in order to assess the ability of the airport to use its airside infrastructure	Employees, Number of runways, Apron size	Passengers, Cargo, LTO	NA
2002-2011	Operational Efficiency of Asia-Pacific airports	Tsui et al. (2014a)	21 Asia-Pacific airports	Aims at estimating the airport efficiency and identifying the key determinants of airport efficiency	number of employees, number of runways, total runway length, and passenger terminal area	Passengers, Cargo, LTO	NA

Table 1 Continued

2006-2007	Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs	Lozano & Gutierrez (2011)	39 Spanish Airports	Estimating airports efficiency in the presence of undesirable effect	Runway Area, Apron Capacity, Number of baggage belts, Gates, check-in-counters	Passenger s, Cargo, LTO	Percentage of delayed flights, Average conditional delay of delayed flights
2009-2014	An evaluation of the operational efficiency of turkish airports using data envelopment analysis and the Malmquist productivity index: 2009–2014 case	Orkcu et al. (2016)	21 Turkish Airports	Aims to analyze the operational efficiency of the airports	Number of runways, dimension of runway units, passenger terminal area	Passenger s, Cargo, LTO	NA
2005-2008	The impact of local air pollution on Italian airport's efficiency	Martini et al. (2011)	33 Italian Airports	Estimating airport's technical efficiency considering the undesirable emissions output	Runway capacity, Number of aircraft parking positions, the terminal area, Number of gates	Passenger s, Cargo, LTO	Emissions during LTO
2009	Capacity shortfall and efficiency determinants in Brazilian airports: Evidence from bootstrapped DEA estimates	Wanke (2012)	63 Brazilian Airports	Aims at analyzing airport efficiency and its determinants by using bootstrapped DEA estimates	Airport Area, Apron, Number of Runways, Total runway length, Number of aircraft parking spaces, Terminal area, Number of parking places	LTO, Passenger, Cargo	NA
2006-2011	Evaluating the multi-period operating efficiency of international airports using data envelopment analysis and the Malmquist productivity index	Ahn & Min (2014)	23 major international Airports	Evaluating airport operating efficiencies, given that air travelers are facing more delays in their travels and suffering from high fares. And, identifying benchmark airports others can emulate.	land area, number of runway units, passenger terminal area, and cargo terminal area	LTO, Passenger, Cargo	NA

Table 2: Airport Efficiency on Financial & Mix Parameters of the airports

Data Period	Title	Authors	Region	Objective	Input Variables	Output Variables	Undesirable output Variable
2009-2012	US airport financial reform and its implications for airport efficiency: An exploratory investigation	Zou et al. (2015)	42 US Airports	Estimating US airport efficiency based on the effect of PFC and AIP grants	labor cost, materials cost, capital cost	passenger enplanements, aircraft operations, amount of cargo handled, non-aeronautical revenue, delays	NA
2000-2004	New evidence on the efficiency of Italian airports: A bootstrapped DEA analysis	Curi et al. (2011)	18 Italian airports	aims to measure the efficiency of Italian airports from the ability to generate financial returns from all the airport activities	Labor Cost, Other costs, Airport Area	Aeronautical Revenue, Non-Aeronautical Revenue	NA
2013	Airport quality and productivity changes: A Malmquist index decomposition assessment	Nicola et al. (2013)	20 Italian Airports	Estimating airport's efficiency based on the airport operations and service quality	Labor cost, Capital, Soft costs (all the other expenses not directly related to capital and personnel)	Workload units (Passengers + Cargo), LTO	Percentage of delayed flights, mishandled bags
2006-2016	Measuring and Explaining Airport Efficiency and Sustainability: Evidence from Italy	Carlucci et al. (2018)	34 Italian Airports	Estimating the overall efficiency of airports and analyzing several factors and their impact on efficiency level	Labor costs, Invested capital, Other expenses	LTO, Passenger, Cargo, Aeronautical revenues, Handling activities revenues	NA
1998-2007	Joint impact of competition, ownership form and economic regulation on airport performance and pricing	Adler and Liebert (2014)	48 European Airports	Analyzing the airport efficiency based on the combined impact of ownership form, economic regulation, and competition on airport performances	staff costs, other operating costs (including materials and outsourcing), runway	number of passengers, commercial air transport movements, tons of cargo	NA
2010-2012	Estimating airport efficiency of New Zealand airports	Tsui et al. (2014b)	11 New Zealand Airports	Aims to explore the efficiency and productivity changes of New Zealand's major airports between 2010 and 2012	Operating Expenses, Number of Runways	Operating Revenues, Passenger, LTO	NA
2000-2006	Two faces of airport business: A non-parametric analysis of the Italian airport industry	Gitto and Mancuso (2012)	28 Italian Airports	Evaluating the impact of regulatory reforms on the technical efficiency of airports	labor cost, capital invested, soft cost, number of workers, runway area, airport area	aeronautical revenues; non-aeronautical revenues; number of movements; number of passengers; amount of cargo	NA

Table 2 Continued

2010	Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique	Lai et al (2015)	24 Major international airports	Evaluating airport's efficiency by the combining use of Analytical Hierarchy Process (AHP) and DEA	Length of Runway, Size of Terminal Area, Number of Runways, Number of employees, Number of gates, Operational Expenses	LTO, Cargo, Passenger, Total Revenues	NA
2005-2009	Incorporating negative externalities into productivity assessments of US airports	Scotti et al. (2014)	44 US Airports	Estimating airport efficiency considering the undesirable outputs by using directional distance function approach	Airport area, runway length, terminal area, number of gates, total airport operating expenses	Passengers, Cargo, LTO	Emissions during LTO, Noise, Delays
1990-1994	Performance based clustering for benchmarking of US airports	Sarkis & Talluri (2004)	44 US Airports	Evaluating airport performance and identifying useful benchmarks for improving the operations of inefficient performers	Operating cost, Employees, Gates, Runways	Operating Revenue, LTO, Passenger, Cargo	NA

Table 3: Summary of the Literature for the Second-stage Analysis

Paper	Region and Years	First stage	Second stage method	Second-stage explanatory variables
Barros & Sampaio (2004)	10 Portuguese airports, 1990 and 2000	BCC DEA	Tobit Regression	Ratio of operational costs to sale, population, Trend, Share, Market share, Regional Share
Barros (2008)	32 Argentine airports, 2003-2007 separately	CCR, BCC DEA	Truncated Regression; Bootstrapped	Trend, Hubs dummy, Workload unit
Malighetti et al. (2009)	57 European airports, 2006	CCR DEA; Bootstrapped	Truncated Regression; Bootstrapped	Connectivity index, Competition between nearby airports, Dominant Carrier ASK percentage, Multi-airport management control dummy
Chu et al. (2010)	8 Asian airports	CCR, BCC DEA	Tobit Regression	Airport staff, airport city GDP, no. of cities navigation, no. of gates
Curi et al. (2010)	36 Italian airports, 2001 and 2003	VRS/CRS DEA; Bootstrapped	Truncated Regression	Labor capital ratio, capital accumulation, privatization dummy, hubs dummy, Partial concession agreement dummy
Gitto et al. (2010)	28 Italian airports, 2000-2006 separately	VRS/CRS DEA; Bootstrapped	Truncated Regression; Bootstrapped	Ownership, handling, seasonality, wealth, hubs dummy
Pareman & Serebrisky (2010)	22 Latin American airports, 2005-2006	CRS/VRS DEA; Bootstrapped	Truncated Regression	Privatization dummy, GDP, Population, Hubs dummy, Share of commercial revenues
Barros et al. (2012)	27 French airports, 2000-2008	BCC, CCR DEA; Bootstrapped	Truncated Regression; Bootstrapped	Trend, Trend ² , Low cost carriers, Market share, Regional share, location dummy
Ha et al. (2013)	11 northeast Asian airports, 1994-2011	CCR DEA	Tobit Regression	GDP, Population, Percentage of International traffic, Workload unit, Runway structure dummy, Seat capacity share of dominant airline, Competition of nearby airport (ln distance)
Merket & Mangia (2014)	35 Italian and 46 Norwegian airports, 2007-2009	VRS DEA; Bootstrapped	Tobit Regression	Hubs dummy, Civil-Military dummy, location dummy, Population, profitability dummy, Competition score
Tsui et al. (2014a)	21 Asia-Pacific airports, 2002 and 2011	BCC DEA	Truncated Regression; Bootstrapped	Trend, Regional GDP, Percentage of international Passengers, hubs dummy, Privatization, operating hours, population, Alliance membership of dominant airlines
Tsui et al. (2014b)	11 New Zealand airports, 2010-2012 separately	SBM DEA	Truncated Regression; Bootstrapped	Population around airport, hubs dummy, operating hours, privatization dummy, Rugby world cup 2011 dummy, Christchurch earthquake dummy

Table 3 Continued

Merkert & Assaf (2015)	30 international airports, 2013	DEA models; Bootstrapped	Truncated Regression; Bootstrapped	Share of non-aeronautical revenue to total revenue, Low cost carrier share, privatization dummy
Zou et al. (2015)	42 US airports, 2009-2012 separately	CCR DEA	Random effects regression	Yearly dummy, hub size dummy, number of passengers served per runway, cargo handled per runway
Millan et al. (2016)	35 Spanish airports, 2009-2011	CRS DEA	Tobit Regression	Workload unit, Percentage of passengers handled by low cost carriers, Cargo and WLU ratio
Orkcu et al. (2016)	21 Turkey airports, 2009-2014 separately	BCC DEA, Malmquist; Bootstrapped	Truncated Regression; Bootstrapped	Population around the airport, hubs dummy, airport operating hours, joint military-civil airport, percentage of international traffic
Wanke et al. (2016)	30 Nigerian airports, 2003-2013	Fuzzy DEA; Bootstrapped	Truncated Regression; Bootstrapped	Wage per employee, Total assets to terminal capacity ratio, Cost per LTO, Regulation dummy, Trend, Trend ²
Recupero (2017)	34 Italian airports, 2006-2016 separately	BCC, CCR DEA	Tobit Regression	Workload unit (WLU), Low cost carriers, Percentage of Cargo traffic to WLU
Nwaogbe et al. (2018)	30 Nigerian airports, 2003-2013 separately	VRS/CRS DEA; Bootstrapped	Censored quantile regression; Bootstrapped	Privatization, Seashore location, Large metropolitan area, Hubs dummy, International flights
Chaouk et al. (2020)	59 Europe and Asia-Pacific airports, 2009 and 2015	CCR DEA	Tobit Regression; Bootstrapped	Air Transport Output index, Market size, Infrastructure, Micro-economic environment, institutions, Safety and Security, Human development index
Ngo et al. (2020)	11 New Zealand airports, 2006-2017	SBM DEA-Window	IV Tobit Regression	Regional guest arrivals, Accommodation, Regional GDP, No. of int. destinations connected by airport, No. of domestic destinations connected by airport, privatization, Low cost carriers

Table 4: Time in Each LTO Phase

LTO cycle	Duration (min)
Take-off	0.7
Climb	2.2
Approach	4
Idle/Taxi	26

Source: (ICAO, 2016)

Table 5: Descriptive Statistics of All Variables

	Type	Variables	Mean	Std. Dev.	Minimum	Maximum
Physical Parameters	Inputs	<i>Materials ('0000) \$</i>	813.71	841.04	21.19	4959.83
		<i>Utilities cost ('0000) \$</i>	1605.14	1710.47	180.99	11521.43
		<i>Labor cost ('0000) \$</i>	7344.41	7135.54	271.55	46560.06
	Carry-Overs	<i>Total Debt ('0000) \$</i>	150950.55	177973.42	0	1093048.7
		<i>IPE ('0000) \$</i>	12800.99	16915.40	-2437.35	125086.57
	Outputs	<i>Non-Aeronautical Revenue ('0000) \$</i>	13229.41	10313.97	1366.82	55556.39
		<i>Aeronautical Revenue ('0000) \$</i>	17239.77	18479.48	1321.27	99319.17
Financial Parameters	Inputs	<i>Full time equivalent employees</i>	621.36	540.58	32	3589
	Carry-Overs	<i>Airport, Acre</i>	4614.8	5309.20	504	33531
		<i>Number of Runways</i>	3.7	1.40	1	8
		<i>Number of Gates</i>	78.82	47.63	14	196
	Outputs	<i>Cargo ('0000) lbs.</i>	1021505.9	1505823.28	0	6422660.8
		<i>Enplanements ('0000)</i>	1299.20	1033.75	146.54	5256.22
		<i>LTOs ('000)</i>	323.91	240.47	44.06	3614.71
Undesirable Outputs		<i>Total Delay, Minutes</i>	254731.27	550383.32	0	3604690
		<i>NOx emissions ('000) kg</i>	2455.54	1853.31	435.93	11356.35
		<i>CO emissions ('000) kg</i>	2300.40	1960.49	340.69	13824.50
		<i>HC emissions ('000) kg</i>	519.90	797.48	29.54	6192.94
Second-stage Explanatory Variables		<i>LN(GDP)</i>	25.16	0.95	22.15	27.39
		<i>LN(Population)</i>	14.03	0.98	11.39	16.13
		<i>Fleet size</i>	122.14	21.13	70.65	177.07
		<i>Percentage of Int. Flights</i>	0.051	0.07	0	0.34
		<i>%College</i>	0.60	0.16	0.18	0.90
		<i>Hub Category Dummy</i>	0.60	0.49	0	1

Table 6: 50 US Airports

Airports Name	IATA Code	Hub Category*	State	County
Hartsfield–Jackson Atlanta International Airport	ATL	L	Georgia	Fulton
Logan International Airport	BOS	L	Massachusetts	Suffolk
Baltimore–Washington International Airport	BWI	L	Maryland	Anne Arundel
Charlotte Douglas International Airport	CLT	L	North Carolina	Mecklenburg
Reagan National Airport	DCA	L	Virginia	Arlington
Denver International Airport	DEN	L	Colorado	Denver
Dallas/Fort Worth International Airport	DFW	L	Texas	Tarrant
Detroit Metropolitan Airport	DTW	L	Michigan	Wayne
Newark Liberty International Airport	EWB	L	New Jersey	Essex
Fort Lauderdale–Hollywood International Airport	FLL	L	Florida	Broward
Daniel K. Inouye International Airport	HNL	L	Hawaii	Honolulu
Dulles International Airport	IAD	L	Virginia	Loudoun
George Bush Intercontinental Airport	IAH	L	Texas	Harris
John F. Kennedy International Airport	JFK	L	New York	Queens
McCarran International Airport	LAS	L	Nevada	Clark
Los Angeles International Airport	LAX	L	California	Los Angeles
LaGuardia Airport	LGA	L	New York	Queens
Orlando International Airport	MCO	L	Florida	Orange
Midway International Airport	MDW	L	Illinois	Cook
Miami International Airport	MIA	L	Florida	Miami-Dade
Minneapolis–Saint Paul International Airport	MSP	L	Minnesota	Hennepin
O'Hare International Airport	ORD	L	Illinois	Cook
Portland International Airport	PDX	L	Oregon	Multnomah
Philadelphia International Airport	PHL	L	Pennsylvania	Philadelphia
Phoenix Sky Harbor International Airport	PHX	L	Arizona	Maricopa
San Diego International Airport	SAN	L	California	San Diego
Seattle–Tacoma International Airport	SEA	L	Washington	King
San Francisco International Airport	SFO	L	California	San Mateo
Salt Lake City International Airport	SLC	L	Utah	Salt Lake
Tampa International Airport	TPA	L	Florida	Hillsborough
Albuquerque International Sunport Airport	ABQ	M	New Mexico	Bernalillo
Anchorage International	ANC	M	Alaska	Anchorage
Nashville International Airport	BNA	M	Tennessee	Davidson
Bob Hope Airport	BUR	M	California	Los Angeles
Cleveland Hopkins International Airport	CLE	M	Ohio	Cuyahoga
Port Columbus International Airport	CMH	M	Ohio	Franklin

Table 6 Continued

Cincinnati/Northern Kentucky Airport	CVG	M	Kentucky	Boone
William P Hobby Airport	HOU	M	Texas	Harris
Jacksonville International Airport	JAX	M	Florida	Duval
Kansas City International Airport	MCI	M	Missouri	Platte
Memphis International Airport	MEM	M	Tennessee	Shelby
Louis Armstrong New Orleans International Airport	MSY	M	Louisiana	Jefferson
Metropolitan Oakland International Airport	OAK	M	California	Alameda
Ontario International Airport	ONT	M	California	San Bernardino
Palm Beach International Airport	PBI	M	Florida	Palm Beach
Pittsburgh International Airport	PIT	M	Pennsylvania	Allegheny
Raleigh-Durham International Airport	RDU	M	North Carolina	Wake
Mineta San Jose International Airport	SJC	M	California	Santa Clara
John Wayne Airport	SNA	M	California	Orange
Lambert-St. Louis International Airport	STL	M	Missouri	St. Louis

*L= Large Hub Airport, M= Medium Hub Airport

Table 7: Overall Efficiency Scores

Airport	Hub	Financial Models				Physical Models			
		Base Model	Model 2	Model 3	Model 4	Base Model	Model 2	Model 3	Model 4
ATL	L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BOS	L	0.65	0.78	0.96	0.98	0.34	0.36	0.49	0.54
BWI	L	0.51	0.51	0.61	0.93	0.41	0.47	0.89	0.99
CLT	L	0.82	0.93	0.79	0.91	0.98	0.99	1.00	1.00
DCA	L	0.50	0.50	0.57	0.64	0.34	0.36	0.53	1.00
DEN	L	0.80	1.00	1.00	1.00	0.44	1.00	1.00	1.00
DFW	L	1.00	1.00	1.00	1.00	0.32	0.50	1.00	1.00
DTW	L	0.47	0.45	0.48	0.51	0.43	0.50	0.67	1.00
EWB	L	1.00	1.00	1.00	1.00	0.94	1.00	0.97	1.00
FLL	L	0.86	1.00	0.90	1.00	0.45	0.52	0.97	1.00
HNL	L	0.56	0.51	1.00	1.00	0.37	0.47	1.00	1.00
IAD	L	0.60	0.52	1.00	1.00	0.24	0.27	0.96	1.00
IAH	L	0.63	0.69	0.79	0.89	0.35	0.53	1.00	1.00
JFK	L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LAS	L	0.54	0.50	0.75	0.75	0.28	0.33	0.90	1.00
LAX	L	1.00	1.00	1.00	1.00	0.44	1.00	1.00	1.00
LGA	L	0.64	0.93	0.67	0.92	0.97	1.00	0.88	1.00
MCO	L	1.00	1.00	1.00	1.00	0.43	0.73	1.00	1.00

Table 7 Continued

MDW	L	0.73	0.60	0.78	1.00	0.93	1.00	1.00	1.00
MIA	L	0.61	0.56	1.00	1.00	0.25	0.26	0.83	1.00
MSP	L	0.94	0.98	0.96	0.97	0.46	0.49	0.71	1.00
ORD	L	0.78	1.00	0.86	1.00	0.74	1.00	1.00	1.00
PDX	L	0.61	0.63	0.97	1.00	0.47	0.55	0.90	1.00
PHL	L	0.53	0.48	0.56	0.57	0.34	0.73	0.67	1.00
PHX	L	0.58	1.00	0.98	1.00	0.38	0.41	0.97	1.00
SAN	L	0.72	0.96	0.71	0.95	0.46	0.56	0.79	1.00
SEA	L	0.72	0.65	0.94	0.96	0.34	0.39	0.93	1.00
SFO	L	0.97	1.00	1.00	1.00	0.24	0.25	0.54	0.57
SLC	L	0.39	0.52	0.38	0.47	0.47	0.73	0.93	1.00
TPA	L	0.56	0.70	0.93	1.00	0.29	0.35	0.81	0.94
ABQ	M	0.78	1.00	0.96	1.00	0.48	0.56	0.91	0.98
ANC	M	0.59	0.62	1.00	1.00	0.50	0.71	1.00	1.00
BNA	M	0.44	0.70	0.81	1.00	0.54	0.71	0.88	0.95
BUR	M	1.00	1.00	1.00	1.00	0.84	1.00	0.98	1.00
CLE	M	0.58	0.76	0.79	0.90	0.34	0.38	0.78	1.00
CMH	M	0.45	0.90	0.83	0.94	0.39	0.45	0.78	1.00
CVG	M	0.28	0.55	0.49	0.85	0.39	0.69	0.76	1.00
HOU	M	0.55	0.85	0.67	1.00*	0.47	0.51	1.00	1.00
JAX	M	0.34	0.56	0.73	0.83	0.50	1.00	0.73	1.00
MCI	M	0.38	0.63	0.76	1.00	0.32	0.83	0.82	1.00
MEM	M	0.63	0.55	1.00	1.00	0.58	0.78	0.96	1.00
MSY	M	0.78	0.85	0.83	1.00	0.89	0.99	0.95	0.99
OAK	M	1.00	1.00	1.00	1.00	0.68	0.81	1.00	1.00
ONT	M	0.41	1.00	1.00	1.00	0.69	0.77	1.00	1.00
PBI	M	0.67	0.95	1.00	1.00	0.82	1.00	1.00	1.00
PIT	M	0.40	0.44	0.82	1.00	0.31	0.74	0.73	1.00
RDU	M	0.51	0.78	0.75	0.88	0.53	0.77	0.81	0.95
SJC	M	0.75	0.67	1.00	1.00	0.67	0.75	0.98	1.00
SNA	M	0.80	1.00	1.00	1.00	0.96	1.00	1.00	1.00
STL	M	0.50	0.42	0.74	0.85	0.33	0.39	0.72	0.86
Overall Avg.		0.67	0.77	0.86	0.93	0.53	0.67	0.88	0.97
L Hub Avg.		0.72	0.78	0.85	0.91	0.50	0.62	0.88	0.97
M Hub Avg.		0.59	0.76	0.86	0.96	0.56	0.74	0.89	0.99
Efficient L Hub		6	11	11	17	2	8	11	26
Efficient M Hub		2	5	8	14	0	4	6	15

Remarks:

-Bolded numbers represent efficient cases

-*Rounded to 1.00 but not exactly equal to 1, and therefore not efficient

Table 8: Efficiency Scores Over Study Period of Financial Model 4

Airports	Hub	Overall	Rank	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
ATL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DEN	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFW	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EWB	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
FLL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HNL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IAD	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JFK	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LAX	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MCO	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MDW	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MIA	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ORD	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PDX	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PHX	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SFO	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
TPA	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BOS	L	0.98	32	0.92	0.92	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MSP	L	0.97	33	0.66	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SEA	L	0.96	34	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.79	0.81
SAN	L	0.95	35	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.82	0.73	0.92
BWI	L	0.93	37	1.00	1.00	0.68	0.66	1.00	1.00	1.00	1.00	1.00	1.00
LGA	L	0.92	38	0.56	0.63	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CLT	L	0.91	39	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.51	0.61
IAH	L	0.88	41	0.77	0.87	1.00	1.00	0.81	0.75	0.84	0.80	1.00	1.00
LAS	L	0.75	46	0.76	0.67	0.74	0.66	0.77	0.83	0.76	0.72	0.77	0.82
DCA	L	0.63	47	0.65	0.70	0.63	0.55	0.58	0.57	0.64	0.66	0.65	0.70
PHL	L	0.57	48	0.48	0.54	0.53	0.52	0.49	0.49	0.53	0.71	0.71	0.65
DTW	L	0.51	49	0.53	0.54	0.51	0.49	0.46	0.50	0.55	0.53	0.46	0.54
SLC	L	0.47	50	0.45	0.44	0.47	0.39	0.40	0.43	0.53	0.44	0.52	0.58
ABQ	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ANC	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BNA	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BUR	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MCI	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MEM	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MSY	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
OAK	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ONT	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PBI	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 8 Continued

PIT	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SJC	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SNA	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HOU	M	1.00*	31	1.00	1.00	1.00*	1.00*	1.00	1.00	1.00	1.00	1.00	1.00
CMH	M	0.94	36	0.66	0.76	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CLE	M	0.90	40	0.68	0.85	0.84	0.89	0.79	1.00	1.00	1.00	1.00	1.00
RDU	M	0.88	42	1.00	1.00	0.71	0.72	0.75	0.84	0.79	1.00	1.00	1.00
CVG	M	0.85	43	0.00	0.56	0.53	1.00	1.00	1.00	1.00	1.00	1.00	1.00
STL	M	0.85	44	0.70	0.78	1.00	0.81	1.00	0.78	1.00	1.00	0.69	0.71
JAX	M	0.83	45	0.58	0.72	0.59	0.73	0.71	1.00	1.00	1.00	1.00	1.00
Overall Avg.		0.93		0.89	0.92	0.93	0.92	0.94	0.94	0.95	0.95	0.94	0.95
L Hub Avg.		0.91		0.89	0.91	0.92	0.91	0.92	0.92	0.93	0.92	0.90	0.92
M Hub Avg.		0.96		0.88	0.93	0.93	0.96	0.96	0.98	0.99	1.00	0.98	0.99

Remarks:

-Bolted numbers represent efficient cases.

-*Rounded to 1.00 but not exactly equal to 1, and therefore not efficient.

Table 9: Efficiency Scores Over Study Period of Physical Model 4

DMU	hub	Overall	Rank	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
ATL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CLT	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DCA	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DEN	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DFW	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
DTW	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EWB	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
FLL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HNL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IAD	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
IAH	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JFK	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LAS	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LAX	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LGA	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MCO	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MDW	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MIA	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MSP	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ORD	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 9 Continued

PDX	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PHL	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PHX	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SAN	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SEA	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SLC	L	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BWI	L	0.99	43	1.00	1.00	1.00	0.87	1.00	1.00	1.00	1.00	1.00	1.00
TPA	L	0.94	47	0.83	0.88	0.70	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SFO	L	0.57	49	0.54	0.56	0.54	0.55	0.55	0.55	0.61	0.57	0.62	0.62
BOS	L	0.54	50	0.42	0.46	0.45	0.55	0.51	0.54	0.54	0.62	0.64	0.66
ANC	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
BUR	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CLE	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CMH	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
CVG	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
HOU	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
JAX	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MCI	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MEM	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
OAK	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ONT	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PBI	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
PIT	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SJC	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
SNA	M	1.00	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MSY	M	0.99	42	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.88
ABQ	M	0.98	44	1.00	0.92	0.87	1.00	1.00	1.00	1.00	1.00	1.00	1.00
RDU	M	0.95	45	1.00	0.97	0.87	1.00	0.84	1.00	0.86	1.00	1.00	1.00
BNA	M	0.95	46	1.00	1.00	1.00	1.00	0.87	0.85	1.00	1.00	1.00	0.79
STL	M	0.86	48	0.72	0.77	0.96	0.71	0.97	0.77	1.00	1.00	0.74	1.00
Average		0.98		0.97	0.97	0.97	0.97	0.97	0.97	0.98	0.98	0.98	0.98
L Hub Avg.		0.97		0.96	0.96	0.96	0.97	0.97	0.97	0.97	0.97	0.98	0.98
M Hub Avg.		0.99		0.99	0.98	0.99	0.99	0.98	0.98	0.99	1.00	0.99	0.98

Remarks:

-Bolded numbers represent efficient cases.

Table 10: Sources of Inefficiency for the Five Least Performing Airports in Financial Model 4

Airports	Labor cost	Utilities cost	Materials cost	Debt	IPE
DCA	-33%	-10%	-62%	-25%	130%
DTW	-31%	-39%	-52%	-48%	95%
LAS	-22%	-10%	-22%	-44%	83%
PHL	-46%	-24%	-38%	-68%	-19%
SLC	-36%	-14%	-83%	-1%	113%

Table 11: Second Stage Truncated Bootstrapped Regression Estimation Results

Variables	Coefficient	t- Value
Constant	0.6447***	10.75
GDP	0.0001***	4.22
Population density	-0.0068**	-2.40
Percentage of acquiring college degree	0.0012***	2.66
Fleet Size	0.0021***	5.87
Int. Share of flights	0.0048***	4.80
Hub Category	-0.1051***	-6.43

*Note: ***, and ** denote 1%, and 5% significance level.*

CHAPTER III
ESTIMATING THE REBOUND EFFECT OF THE US ROAD
FREIGHT TRANSPORT

I write my paper from the scratch. I use secondary data for my first paper. I collected secondary data from different sources including the Bureau of Labor Statistics, Bureau of Transportation Statistics, the World Bank, etc. After carefully reviewing the existing literature, I use the most popular method to obtain my objectives. I also use the newer method to validate my results. Based on the analysis, I discuss the potential implications and try to give some recommendations.

Abstract

The U.S. freight sector has continued to expand over the past decades and made a key role in linking the nation's economic activities. In 2018, nearly 5.3 trillion ton-miles of goods were moved in the nation with trucks as the dominant mode. The increase of road freight transport presumably maintains given the surging development of eCommerce and easiness of online shopping. Such growth in the freight demand likely increase the fuel used in the road freight and result in more greenhouse gas (GHG) emissions. To mitigate the upward trend of energy use and GHG, various policies have been introduced to improve fuel technology and economy. Such improvements may initially lower freight fuel use and reduce emissions. However, rebound effect may prompt more energy consumption in the freight sector and may offset the efficiency gains. We use eight fuel cost models to estimate the U.S. road freight sector's rebound effect in 1980-2016. Furthermore, we applied a recently developed data envelopment analysis for time series data to determine the annual rebound effect in the road freight sector. Our results suggest an average rebound effect of 8.8% in the short-run and 6.9% over the longer period in the U.S. road freight sector. The rebound effect of the U.S. road freight sector increased over time but was considerably less than the rebound effect of the European countries and other developed countries. The increase in the rebound effect could be related to the shipping distance, type of commodity, and modal share over the study period. Our findings suggest that policymakers need to consider the rebound effect in the design of related policies to mitigate the rebound effect.

Keywords: Energy efficiency, Rebound effect, US road freight transport , Time series data

Introduction

The United States (US) freight sector has continued to expand over the past decades thereby linking the nation's economic activities. In 2018, nearly 5.3 trillion ton-miles of goods were moved with trucking as the dominant mode (BTS, 2018a). Given the surging development of eCommerce and easiness of online shopping, this growth is expected to sustain. The freight growth is partly influenced by the decoupling of freight activity from GDP in OECD countries, resulting from economic restructuring and the outsourcing of manufacturing to emerging economies (McKinnon, 2007). Increased consumption of goods tends to increase freight energy consumption that is also affected by fuel efficiency, road condition, labor force, and the load factor of heavy goods vehicles (HGV) (Sorrell, 2007). The US transport sector is the second-largest energy user among major economic sectors, accounting for more than 28% of all energy consumption in the US (BTS, 2018b). Among transport sectors, road freight transport has the highest energy use (Sorrell and Stapleton, 2018) and constitutes one-third of transport energy consumption in the US (IEA, 2016).

Energy consumption from rising freight transport results in increased greenhouse gases (GHG) emissions as an undesirable output. The US transport sector surpassed the electric power sector in 2016 in becoming the top source of national GHG emissions. Freight trucks produced about 23 percent of US all transport-based GHG emissions (EPA, 2017; C2ES, 2013). Therefore, reducing energy consumption through energy efficiency improvement is a primary focus of policymakers (Sorrel and Stapleton, 2018). To mitigate the rising trend of energy use and carbon emissions, the US government implemented

national energy policies like the Energy Independence and Security Act in 2007, and the Clean Air Act in 2012 regulations aimed at improving fuel efficiency (gallons /1000 ton-kilometer) and reducing GHG intensity (Metric Tons CO₂ eq./ ton-kilometer) of heavy goods vehicles (HGVs) (EPA and NHTSA, 2011a; EPA, 2007; 2012).

The effects of the governmental efforts to lower GHG emissions are unclear, however, as anticipated reductions in energy use may not occur. Presumably, when the effective price of energy service decreases, more people may be attracted to use the same energy-efficient technology in turn actually increasing total energy use (Sorrell and Dimitropoulos, 2008). Accordingly, energy efficiency improvement that encourages more energy consumption may offset the anticipated energy savings. This phenomenon is the so-called *rebound effect*. Further, increases in savings as a result of the adoption of energy efficiency improvement technology release funds that can be expended on other goods and services. This phenomenon is also included in the rebound effect. Moreover, the rebound effect accounts for drivers' asymmetric behavior to energy price increase and decrease both in the short-run and long-run. Increase in energy price may decrease the rebound effect while energy price reduction may amplify the rebound effect (Lin & Li, 2014; Stapleton et al., 2016).

Empirical studies regarding the rebound effect in the road freight transport sector are numerous. Small and Dender (2007) found the rebound effect from the improved fuel efficiency in the US passenger transport sector. Llorca and Jamasb (2017) found the presence of the rebound effect in the European Union (EU) road freight transport after the EU adopted air quality, energy security, and climate change policy. Sorrel and Stapleton (2018) estimated the rebound effect in the UK's road freight sector by using static and

dynamic models. However, an updated study on the rebound effect and efficiency associated with US road freight transport is still lacking. Hence, further research in this regard is warranted. Therefore, the objective of this study is to analyse the rebound effect for US road freight transport due to government policies aimed at reducing energy consumption and GHGs emissions. We also aim to estimate the rebound effects considering the carriers' asymmetric energy price responses.

Literature Review

William Jevons was the first person who showed that energy efficiency improvement can lead to fewer energy savings due to behavioral and systematic responses (Jevons, 1866). Jevons in his seminal paper, "the coal question," argued that "it is ridiculous to reduce fuel consumption through using it economically and instead the opposite is true". This phenomenon is known as the Jevons Paradox. Clark and Foster (2001) illustrated Jevons argument on energy efficiency and consumption using an example of iron furnaces. The example specified that if the furnace increases the profitability by reducing the amounts of coal in the furnace for maintaining the same level of output, the new capital investment will be attracted that could result in increased iron production and lowered final product (iron) price. Thus, the increased number of furnaces could offset the decreased average consumption of each furnace, which would eventually result in increased domestic coal consumption.

Khazzoom (1980) studied the components of Jevons Paradox and showed that the demand for energy is price elasticity in the long run, implying that the rebound effect holds if sufficient time span is considered. When actual energy savings are higher than the

expected savings, the rebound effect is then negative. The price effect of an energy efficiency improvement is known as the direct rebound effect which includes both the substitution and income effects. The effect of spending the extra income from energy efficiency on the other goods or services is known as the indirect rebound effect (Sorrell, 2007).

Table 12 summarizes previous studies that have examined the rebound effect in the freight transport sector *[Insert Table 12 here]*. Ruzzenenti and Basosi (2017) concentrated on the energy efficiency of the freight sector in the EU as it is a pillar of the EU's strategy to meet the Kyoto protocol agreement. However, the increasing freight demand resulting from the rebound effect became a barrier to the goal of reducing carbon emissions along with increasing energy efficiency. The estimated rebound effect is negative varying between -74% and -146%, which means that actual energy savings are higher than the expected savings. Llorca and Jamasb (2017) also highlighted the effectiveness of the EU's newly adopted energy and environmental policies as a way of promoting energy consumption reduction to reduce the dependency on fossil fuels and mitigate GHGs emissions. They focused on the actual energy savings by considering the rebound effect in 15 European countries' road freight transport sector. The average estimated direct rebound effect was 3.8%. The highest rebound effect exists in Sweden at 7.9%. More fuel-efficient countries, such as Austria, Germany, and Denmark, have a larger rebound effect compared to least fuel-efficient countries like Poland and Hungary. Matos and Silva (2011) estimated the rebound effect in Portugal's freight transport sector. They estimated the direct rebound effect to be over 24%. A recent study conducted by Sorrell and Stapleton (2018), measured the rebound effect in the UK's freight transport, as HGV's energy consumption is

increasing more rapidly than passenger transport. They found the estimated average direct rebound effect to be 49% which means that a 1% increase in energy efficiency improvement will reduce energy consumption by about 0.5%.

Some researchers have paid attention to the rebound effect in some emerging economies or developing countries. Wang and Lu (2014) estimated the direct rebound effect on China's road freight transport that is the country's largest energy consumption sector. The analysis showed that the direct rebound effects for eastern, central, western regions, and entire China are 52%, 80%, 78%, and 84%, respectively. A more recent study by Jin and Kim (2019) estimated the macroeconomic growth energy rebound effect of South Korea to be on an average 1%, which is facing a serious environmental situation with its rapid growth in carbon emissions over the last 20 years.

A few studies focus on the asymmetric nature of the rebound effect with respect to changes in energy price. Bentzen (2004) argued that asymmetric price responses should be included in models that examine the rebound effect, as energy use is closely related to responses to energy price changes. He estimated the rebound effect in the US manufacturing sector to be around 24%. Stapleton et al. (2016) considered the asymmetric price responses in estimating the rebound effect in Great Britain's personal automobile transport, and suggested an overall increase in the rebound effect for fuel price decrease. Lin & Li (2014) incorporated asymmetric price responses in the model specification to estimate the rebound effect in China's heavy industry, and found an increased rebound effect for the energy price decrease.

Conceptual Framework

Improving energy efficiency for an energy service could decrease the effective price of that service, and presumably, result in a rebound effect. Figure 4 explains the rebound effect where the vertical axis denotes energy consumption, and the horizontal axis denotes energy service demand (Mizobuchi, 2008) *[Insert Figure 4 here]*. Line ε_0 represents the initial level of efficiency of the energy service. An improvement in energy efficiency from ε_0 to ε_1 can reduce the energy consumption from E_0 to E_1 when the demand level of energy service is constant. However, consumers may increase their energy service demand because of the reduction in energy service costs, which leads the energy consumption to reduce from E_0 to E_2 instead of E_1 . Hence, the actual savings will be less than the potential savings, which eventually introduce the rebound effect. The following equation (1) can express the rebound effect:

$$\begin{aligned} \text{Rebound effect (RE)} &= \frac{\text{rebound energy consumption}}{\text{potential energy savings}} * 100\% \\ &= \frac{\text{potential energy savings} - \text{actual energy savings}}{\text{potential energy savings}} * 100\% \\ &= \frac{E_2 - E_1}{E_0 - E_1} * 100\% \\ &= 1 - \frac{E_0 - E_2}{E_0 - E_1} * 100\% \end{aligned} \quad (1)$$

Equation (1) explains that if the rebound effect is 20%, then 20% of the expected energy savings are offset by the increased consumption. Thus, this equation can be used to estimate the energy rebound effect by making an energy demand comparison of before and after energy efficiency improvement. But other factors may influence energy consumption. Failure to control other factors related to energy consumption may lead to a biased estimate

of the rebound effect. To address those factors, various definitions of a rebound effect have been introduced in the previous studies.

Some methods apply proxy variables to estimate the rebound effect (Sorrell and Dimitropoulos, 2008; Sorrell and Stapleton, 2018). The following equations denote a common definition of rebound effect estimation:

$$RE = n_{\varepsilon}(S) = \frac{\partial \ln S}{\partial \ln \varepsilon} = 1 + n_{\varepsilon}(E) \quad (2)$$

In equation (2), $n_{\varepsilon}(E)$ is the efficiency elasticity of energy demand, and $n_{\varepsilon}(S)$ is the efficiency elasticity of an energy service. Energy savings due to energy efficiency improvement are only completely effective when the efficiency elasticity of demand for the energy service is zero. Then, the efficiency elasticity of demand for energy is equal to minus one, thus $n_{\varepsilon}(S) > 0$ or $|n_{\varepsilon}(E)| < 1$ implies a positive rebound effect. Energy efficiency ε is the ratio of useful energy service (S) and energy inputs (E). With the improvement of energy efficiency, energy consumption will decline.

Some researchers use negative price elasticity of energy service demand to estimate the direct rebound effect (Berkhout, Muskens, and W. Velthuisen, 2000; Binswanger, 2001). The equation is stated below:

$$RE = -n_{P_S}(S) = -\frac{\partial \ln S}{\partial \ln P_S} \quad (3)$$

P_S and S in equation (3) are energy cost and service demand. Data for P_S and S can be more easily obtained, hence the relative popularity of this approach. However, this definition requires rigorous data for estimating energy service cost, as energy price are treated as an exogenous variable. Thus, energy cost depends on the changes in energy prices and energy efficiency, which is $P_S = P_E / \varepsilon$, where P_E is the energy price.

Another form of presenting rebound effect in price elasticity and energy service demand is presented as follows:

$$RE = -n_{P_E}(S) = -\frac{\partial \ln S}{\partial \ln P_E} \quad (4)$$

Like equation (3), equation (4) also uses negative price elasticity of energy service demand to estimate the rebound effect.

If we assume energy efficiency ε to remain a constant, then the rebound effect is equal to the price elasticity of energy consumption ($n_{P_E}(E)$) (Frondel, Peters, and Vance, 2008; Saunders, 2005; Sorrell and Stapleton, 2018).

$$RE = -n_{P_E}(E) = -\frac{\partial \ln E}{\partial \ln P_E} \quad (5)$$

Researchers nowadays use the energy price elasticity of energy service to estimate the direct rebound effect (Matos and Silva, 2011b; Sorrell and Stapleton, 2018; Llorca and Jamasb, 2017).

However, Jin & Kim (2019) argued over the existing rebound effect definitions. According to them, if the energy intensity of a sector is highly volatile over time, traditional rebound estimation overestimates the actual rebound effect. Thus, they proposed the following equation (6):

$$RE_t = \frac{E_{t,actual}}{E_{t,potential}} - 1 \quad (6)$$

Where, $E_{t,actual}$ refers to actual energy consumption. $E_{t,potential}$ refers to potential energy consumption calculated by the data envelopment analysis (DEA).

Methods

Equation (3) is used in our initial estimation of the rebound effect, while *Equation (6)* is an additional estimation served as a basis of comparison. Following prior studies (Matos and Silva, 2011; Ruzzenenti and Basosi, 2017), road freight activity is measured in ton-kilometers (Tkm), i.e., tons of goods moved to the distances. Road freight levels can be influenced by different economic variables i.e. factors of production (labor force, and vehicle purchases), fuel cost (P_s), and gross domestic product (GDP) of the region. Fuel price (P_e), fuel cost (P_s), GDP (y), and energy efficiency of goods moved (ϵ) are the most widely used variables to estimate rebound effect in the freight transport sector (Sorrell and Stapleton, 2018; Matos and Silva, 2011; Jin and Kim, 2019).

The primary hypothesis tested here is that of no rebound effect associated with efficiency improvement in the US road freight transport sector. For modeling, we considered fuel cost models with their static and dynamic versions for short-run and long-run rebound effect estimations (Sorrell & Stapleton, 2018). Static models estimate distance travelled as a function of the same period explanatory variables. Since responses to efficiency improvements and fuel price changes take time, static models may not fully capture these effects. Thus, we also estimate dynamic versions of each model by taking current and historic explanatory variables.

Static fuel cost (SF) model is formed as:

$$\ln Tkm_t = \beta_0^{SF} + \beta_1^{SF} \ln Y_t + \beta_2^{SF} \ln P_{st} + \mu_t \quad (7)$$

Dynamic fuel cost (DF) model is formed as:

$$\ln Tkm_t = \beta_0^{DF} + \beta_1^{DF} \ln Y_t + \beta_2^{DF} \ln P_{St} + \beta_3^{DF} \ln Tkm_{t-1} + \mu_t \quad (8)$$

In the static model, the elasticity of Tkm with respect to fuel cost ($n_{P_s}(Tkm)$) is given by the coefficient β_2^{SF} . In the dynamic model, the elasticity is given by $((\beta_2^{DF} / (1 - \beta_3^{DF}))$. Three variables are added to equation 8 versus equation 7 (a Year2012 dummy, ultra-low Sulfur Diesel (ULSD) dummy, and manufacturing share of GDP. A total of eight different models are estimated, including the base static model, three fuel cost static models, the base dynamic model, and three fuel cost dynamic models, with different combinations of the variables presented in equations (7) and (8).

The selection of the models relies upon the results of a series of diagnostic tests, including serial-correlation tests, and heteroscedasticity test for the error terms of each model. An endogeneity test is also performed for the GDP variable, as we anticipate that the residual of Tkm might be correlated with GDP. They might be related to some common factors, i.e., fixed assets, the total number of employees, unemployment rates (instrumental variables). We also perform fit tests to find the compatibility of the instrumental variables in identifying the endogeneity issue of GDP. Three types of tests are used which are the test on under identification, weak identification, and over identification problems. Under identification test checks if the number of instrumental variables is less than the number of endogenous variables. Weak identification test is used to checks for the explanatory power of the instrumental variables for the endogenous variable, whereas over identification test is used to check whether the instruments are correlated with the error term or not. If any of the instruments are correlated with the error term, then those instruments are not considered as good instruments. The null hypothesis is that the instruments are valid.

An economy-wide rebound effect methodology proposed by Jin and Kim (2019) is used to serve as a complementary to the structural equation model results. First, the annual efficiency score is estimated based on a non-parametric data envelopment analysis (DEA) method using the slack-based DEA model (Tone and Tsutsui, 2003). In this method, the sector's decision each year is considered as one decision-making unit (DMU) with Tkm as the output and technological progress of the freight sector and energy consumption as the inputs. Technological progress is estimated from a Cobb-Douglas (C-D) production function comprising labor in the freight sector and new vehicle purchases as factors of production for Tkm. The output-oriented slack based DEA model is then used as follows:

Let,

$$X_{nt} = (X_{1t}, X_{2t}, \dots, X_{nt})$$

$$Y_{lt} = (Y_{1t}, Y_{2t}, \dots, Y_{lt}), t=1, 2, 3, \dots, t$$

$$\text{Minimize, } \rho = \frac{1 - \frac{1}{N} \sum_{n=1}^N \frac{S_n^x}{S_{n0}^x}}{1 + \frac{1}{L} \sum_{l=1}^L \frac{S_l^y}{Y_{l0}}} \quad (9)$$

Subject to,

$$\sum_{t=1}^t \lambda_t X_{nt} + S_n^x = X_{n0} \quad (10)$$

$$\sum_{t=1}^t \lambda_t Y_{lt} - S_l^y = Y_{l0} \quad (11)$$

$$\sum_{t=1}^t \lambda_t \geq 0 \quad S_n^x, S_l^y \geq 0 \quad (12)$$

Where ρ is the energy efficiency score with $0 < \rho \leq 1$. There are total t DMUs. X_{nt} , Y_{lt} , S_n^x , and S_l^y are inputs, outputs, slack vectors of input excesses, and output shortages,

respectively. X_{n0} , and Y_{l0} are the input and output values of the first DMU at t period. λ_t is the estimated weight vector which maximizes the linear combination of input and output vectors. After efficiency score estimation, we can measure the overspent energy consumption based on equation (13) defined by Jin and Kim (2019) to determine annual rebound effect:

$$E_{t,potential} = \text{efficiency}_t * Tkm_t * EI_t \quad (13)$$

Where efficiency_t is the efficiency score found from the DEA for year t. EI_t represents energy intensity which can be derived from dividing Tkm by freight energy consumption. Finally, equation (6) is used to estimate the yearly rebound effect.

Rebound Effect Under Asymmetric Energy Price Responses:

The definition of the rebound effect is related to the increase in energy demand with a corresponding decrease in the effective energy price. A few studies, such as Gately & Huntington (2002), Bentzen (2004), and Lin & Li (2014), showed that consumers would behave asymmetrically to price increase and decrease. Failure to manage this asymmetry would result in biased estimation of the rebound effect (Fronzel & Vance, 2013). Therefore, we further decompose the per gallon fuel prices to re-estimate the asymmetric price response.

We follow the decomposition technique proposed by Gately & Huntington (2002). The original fuel prices can be decomposed into maximum historical prices ($\max[\ln(P_{F,t})]$), cumulative sub-maximum price recoveries ($\text{rec}[\ln(P_{F,t})]$), and cumulative price decreases ($\text{dec}[\ln(P_{F,t})]$) as follows:

$$\ln(P_{F,t}) = \max[\ln(P_{F,t})] + \text{dec}[\ln(P_{F,t})] + \text{rec}[\ln(P_{F,t})] \quad (14)$$

Where,

$$\max[\ln(P_{F,t})] = \max [\ln(P_{F,1}), \ln(P_{F,2}), \ln(P_{F,3}), \dots, \ln(P_{F,t})] \quad (15)$$

$$dec[\ln(P_{F,t})] = \sum_{i=1}^t \min (0, \{\max[\ln(P_{F,t-1})] - \ln(P_{F,t-1})\} - \{\max[\ln(P_{F,t})] - \ln(P_{F,t})\}) \quad (16)$$

$$rec[\ln(P_{F,t})] = \sum_{i=1}^t \max (0, \{\max[\ln(P_{F,t-1})] - \ln(P_{F,t-1})\} - \{\max[\ln(P_{F,t})] - \ln(P_{F,t})\}) \quad (17)$$

Each year fuel price (\$/gallon) is decomposed to find price decreases and recoveries. After the decomposition, recovery fuel price and decrease fuel price are used to generate P_e and P_s . These newly generated variables are used to re-produce the static and dynamic models in equations (7) and (8) to estimate the rebound effects for the new fuel prices.

Variables and Data

Fuel price accounts for the majority of the freight carrier operating costs. A fuel price shock can have a drastic and rapid impact on overall consumption. Thus, fuel price is the most influential variable for modeling in the freight transport sector's rebound effect. Fuel price (P_e) is measured as the price per megajoule (MJ) of energy consumption. GDP growth measures the economic output of a region. Along with fuel price and GDP, factors of production are also considered as inputs regarding freight demand.

The energy efficiency (ϵ) of goods moved is defined as Tkm divided by freight energy consumption. The fuel cost per Tkm (P_s) is primarily influenced by how much it costs to travel one kilometer and how much can be carried at once. Therefore, fuel price and freight energy consumption positively affect the cost of transporting one Tkm. Hence, P_s is defined as dividing P_e by ϵ . An additional variable (following Sorrell and Stapleton,

(2016)) is manufacturing's share of US GDP, as there has been some decoupling of freight activity from GDP in the recent past because of economic restructuring and outsourcing of manufacturing to emerging economies (McKinnon, 2007).

The Year2012 dummy variable is included to capture the potential influence of the Clean Air Act 2012 as more stringent regulations for cleaner highway vehicles are implemented under this act from 2012 (EPA, 2020). Also, the variable of Tkm published at the US Bureau of Transportation Statistics (BTS) is estimated using two different methods before and after 2012. The estimate of Tkm up to 2011 is based on the freight analysis framework 3 (FAF3) that considers the difference between the total of all modes, and the sum of other modes (BTS, 2018c). The 2012-2016 data is tabulated using the FAF4 developed by federal highway administration (FHA) and the Oak Ridge National Lab (ORNL) (2019). The dummy variable has the value of 1 after 2012, otherwise 0.

An additional dummy variable accounts for the policy-driven legal imposition of ultra-low sulfur diesel (ULSD) use for freight transport starting in 2006. ULSD is essentially a cleaner for the environment and better for the engine's fuel economy. Beginning in 2006, the environmental protection agency (EPA) began to phase-in more strict regulations to lower the amount of sulfur in diesel fuel to 15 ppm (EPA, 2006). Therefore, it is recommended to use in all highway diesel vehicles and engines. It might have stimulated the trucking companies to use more energy to cover the greater distances.

Time series data are collected from various sources for the period 1980-2016. Per capita GDP is collected from the world bank (World Bank, 2019). Manufacturing value shipments data are collected from the US Census Bureau (2019). The instrumental variables for the endogeneity test of GDP are collected from two different sources. Data

on the unemployment rate and the total number of employees are collected from the US Bureau of Labor Statistics (2019a; 2019b). And data on the value of fixed assets is collected from the Bureau of Economic Analysis (2019). All other freight-related data (Tkm, energy consumption, fuel prices, freight labor & number of new vehicles purchases each year) are collected from the BTS (2018c) *[Insert Table 13 here]*.

Empirical Results

Diagnostic tests indicate heteroscedastic for both the static 1 and dynamic 1 models *[Insert Table 14 here]*. Two static models (static 1 and static 4) exhibit endogeneity issues as independent variables are correlated with the residue terms. In a broader sense, the unemployment rate, fixed assets, and the total number of employees are related to both GDP and Tkm variables. The static models also have serially correlated error terms as indicated by the Durbin-Watson (DW) d- As do dynamic models 1 and 4 based on the DW h-statistic Accordingly, to correct for related serial correlation and heteroscedastic disturbance terms, a two-stage least squares (2SLS) estimation is applied with heteroskedastic and autocorrelation consistent (HAC) robust corrections (Baum et al., 2015).

Table 15 shows some fit tests for the instrumental variables in each of the 2SLS models *[Insert Table 15 here]*. The Anderson-Canon LM statistic shows that the under-identification issue is not detected in any of the estimated models because the null hypothesis of under identification problem is rejected in all 2SLS models. There is also no weak identification issue found. As the maximal IV size is less than the Cragg-Donald Wald F statistic indicating that the instrumental variables have strong explanatory power

for the endogenous variables. The test for over identification, the Hansen J statistic, shows that the null hypothesis cannot be rejected. Hence, the instruments of all the models are valid and are not correlated with the error term in the system. Overall, the fit tests of the instruments indicate that fixed assets and the total number of employees are valid instruments for the endogenous GDP.

Table 16 presents 2SLS results of the static fuel cost models *[Insert Table 16 here]*. In the base static model, both GDP and fuel cost are statistically significant, suggesting both have an impact on freight ton-kilometers (Tkm). A 1% increase in GDP increases Tkm (more Ton-kilometers) by 0.53%. In contrast, a 1% increase in fuel cost decreases Tkm by 0.14%. In static model 2, the Year2012 dummy variable is added to the base model with all other variables remaining significant. A 1% increase in the fuel cost now decreasing Tkm by 0.064% which is less than half the impact in the base model. The Year2012 dummy is statistically significant and captures the potential impacts of the data collection method as well as the influence of the Clean Air Act. For model 3, all other variables are statistically significant. The impact of fuel cost again decreases to -0.121. In static model 4, the ULSD dummy is insignificant while the remaining variables are still significant. The rebound effects for the three static models are 6.4%, 12.1%, and 8%, respectively. Hence, the US road freight sector has an average 8.8% rebound effect in the short run based on the results of the three static models. An average of results from the three static models also indicates that a 1% increase in fuel efficiency decreases fuel consumption by 0.912%.

Table 17 summarizes the 2SLS estimation results of the four dynamic fuel cost models *[Insert Table 17 here]*. The lag dependent variable is significant in three of the four dynamic models. Also, GDP and fuel cost are significant in three of the four dynamic models. However, model results indicate that the impacts of both GDP and fuel cost on Tkm are lower in the long run than in the short run. The Year2012 dummy has an average percentage negative impact on Tkm across the four dynamic models of 16.8%. Manufacturing share is significant in dynamic models3 and 4. As the long-run elasticity of goods moved in the dynamic framework is dependent on the significant estimates of fuel cost and lag term, we calculate the estimates for the rebound effect to be 7.6%, and 6.3% in dynamic 2 and 4 models where both lag term and fuel cost are significant. Averaging across these values gives us a mean estimate of 6.9%, which means that in the long run a 1% increase in fuel efficiency decreases fuel consumption by more than 0.9%.

Our estimated rebound effects imply that a proportion of the potential energy and carbon savings from the improved efficiency in US road freight has been offset by increased freight activity (more ton-kilometers). Comparing the dynamic models to the static models, there is some variability in the results. It is seen that dynamic models produce smaller rebound effects than the static models. It suggests that reliance upon static models can lead to larger price elasticities (Goodwin et al., 2004).

Figure 5 illustrates the annual rebound effect estimated from the robust SBM DEA model *[Insert Figure 5 here]*. On average, the rebound effect of the US road freight transport is 5.5% which is 20.3% less than our estimated dynamic fuel cost models. It is seen that the annual rebound effect was less than 5% in the period 1980-2005. From 2006

through 2010, it typically ranged between 5% and 10%. However, from 2012-2016, it dramatically increased to the 21-26% range.

The price decomposition results are illustrated in figure 6, where X-axis denotes the year and Y-axis denotes the natural logarithm of decomposed fuel prices *[Insert Figure 6 here]*. By using these new price series, the re-estimated results for the dynamic and static models are presented in Table 18 *[Insert Table 18 here]*. The table represents the rebound effects of recovery fuel price (P_{rec}) and decrease fuel price (P_{dec}) along with the original fuel price estimate for both static and dynamic models. All variables in the P_{rec} fuel cost are statistically significant. The rebound effects are averaged 7.3% and 5% for the static and dynamic models. These averages are lower than the original fuel price average rebound effect (8.8% in static, 6.9% in dynamic), suggesting the freight carriers use less energy as with the price increase and result in a lower rebound effect. In the P_{dec} cases, the average rebound effects of the static and dynamic models are 9.5%, and 7.1%, which are higher than the original rebound effect estimates, implying the increase of fuel consumption in responding to reduction in fuel price. Our estimates are in line with several previous studies. Bentzen (2004) found a rebound effect of 24% from the energy price decrease in the US manufacturing industry. Lin & Li (2014) also found an increased rebound effect for the energy price decrease in the Chinese heavy industry.

Our estimated short-run rebound effect is higher and our long-run estimation is lower than those of Small and Dender (2007) who found the rebound effect for the US passenger transport to be 4.5% and 22.2% in the short- and long-run from 1966-2001. Comparing to other countries, the rebound effect of US road freight is higher estimates for

European countries which is on average 3.8%, estimated by Llorca and Jamasb (2017). However, Portugal and the UK's road freight sector have significantly higher estimates than the US (Matos and Silva, 2011; Sorrell and Stapleton, 2018). China has the highest rebound effect of 84% in the road freight sector (Wang & Lu, 2014). Overall, it is seen that the rebound effect is inconsistent over different geographic locations. It is also varied over time, as we have seen from our yearly rebound estimation that there is a surge of rebound effect in the US road freight transport after 2011. The possible explanations of this high variability of the rebound effect of the road freight sector over the years might lie in the following reasons.

First, the types of commodity to be transported by freight transport can be an important factor for the high variability of freight rebound effect across time. For example, according to Li et al., (2011), bulk commodities like log, lumber, and textiles are shown to be less elastic than non-bulk commodities like paper, plastic, and rubber products. Hence, our estimation results reflect the situation that the Tkm generated by the trucking is mostly associated with bulk commodities *[Insert Figure 7 here]*. It shows that most of the bulk commodities e.g., meat, seafood, coal, motorized vehicle machinery, among others moved by road freight transport in the US has increased over time. Hence, the rebound effect is slightly higher in the short run but lower in the long run. The shift in the composition of freight movement could be due to changes in shipping distance including origin and destinations and to changes in the sectoral composition and location of economic activity (for example, primary producers of certain products e.g., seafood, red meat, dairy and

horticulture, log and lumber, among others have perhaps become increasingly geographically concentrated).

Second, Christdis and Leduc (2009) stated that shorter shipping distances tend to be less elastic than long shipping distances. According to US DOT (2010) and Winebrake (2009), the majority of the HGV shipping in the US is for shorter distances i.e. less than 500 miles, which may explain smaller rebound effects in the US road freight transport. Also, distance is closely related to the availability of competing modes for commodity shipping.

Third, the availability of alternative modes might have an impact on freight elasticity. This availability is also dependent on factors like regional infrastructure and shipping distances. Christdis and Leduc (2009) showed, generally, the shorter the shipping distance, the greater the possibility of only one modal option availability. Rich et al. (2011) showed that, when the shipping distance is longer, rail and barge are often available alternatives, which increases the ability to respond to price changes (i.e, elasticity estimates increase). Specifically, rail availability as an alternative to the truck allows the companies to consider the cross-price elasticities between modes. Winebrake et al., (2012) said that smaller elasticities hint a potential shift from rail to truck in the US due to changes in HGV freight prices due to increased fuel efficiency. Lower freight elasticity found in our study indicates there might be a shift of shipping from rail to truck to accommodate the relative growth in shorter shipping distance. However, the large-scale shipments weighing between 25 to 40 tons and greater than 500 miles are more suited to rail (EPA and NHTSA, 2011).

When travel cost decreases in the US road freight sector, there might have less incentive to fully pack trucks, which eventually increases energy intensity along with Tkm (Winebrake et al., 2012). It explains the volatile nature with a boost in the energy intensity of the US road freight sector *[Insert Figure 8 here]*. Moreover, less-efficient road speed or congested roadways tend to decrease fuel efficiency thereby increasing energy intensity. The change of route can also increase total miles traveled and energy intensity.

Conclusion

One of the main objectives of energy and emissions policies is to reduce energy consumption in the energy consumptive sectors like the road freight sector. Energy consumption reduction can be done through fuel economy improvement. However, such improvements lower the marginal cost of supplying energy service that may in turn increase energy consumption thus eventually offsetting the expected energy efficiency gains (i.e., creating a rebound effect).

We estimate the rebound effect in the US road freight sector for the period 1980-2016. Based on eight four static and four dynamic fuel cost models, our results show an average rebound effect of 8.8% in the short-run and 6.9% in the long-run. We find that the rebound effect is less than 5% in the initial years. However, it increases to 10% in 2007, raising to an average of 22.2% after 2011. We also checked the rebound effect under asymmetric energy price responses. We found that the rebound effect increases with price declines and decreases with price increases. It explains the existence of rebound effects in the US road freight sector even with the energy price changes over the years.

Comparing our estimation to the existing literature, we found that the rebound effect has increased in the US road freight sector in the short run. It is significantly less than the rebound effect found for the UK's road freight sector. Moreover, it is sufficiently less than that of other European countries, and other developed countries i.e. China, Canada, and Australia. We discussed this variability of the US rebound effect in terms of several factors like commodity types, shipping distance, modal share, and geographical location.

Our results have important policy implications. Policies attempt to reduce energy consumption and its byproduct. The estimated rebound effect proves to be a deterrent to the energy efficiency policies where the actual energy consumption exceeds the consumption expected from the policies. Hence, policymakers need to design policies not only to minimize the energy use but also to take the rebound effect generated from policies into account to better gauge the impact of related policies. Specific policies like Cap-and-trade schemes can be used to tackle the integrated rebound effect (Llorca and Jamasb, 2017). In addition, policymakers can consider welfare gains and losses from the related policies as a part of their design that can identify the economic efficiency of such policies.

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Appendix B

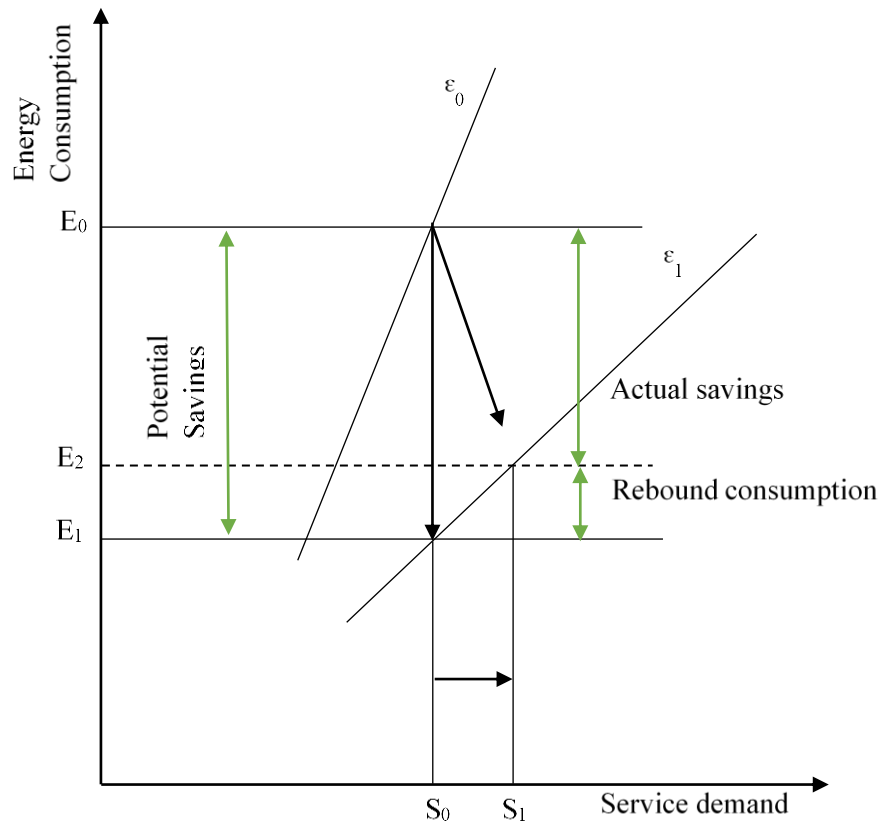


Figure 4: Graphical Representation of the Rebound Effect (*Mizobuchi, 2008*)

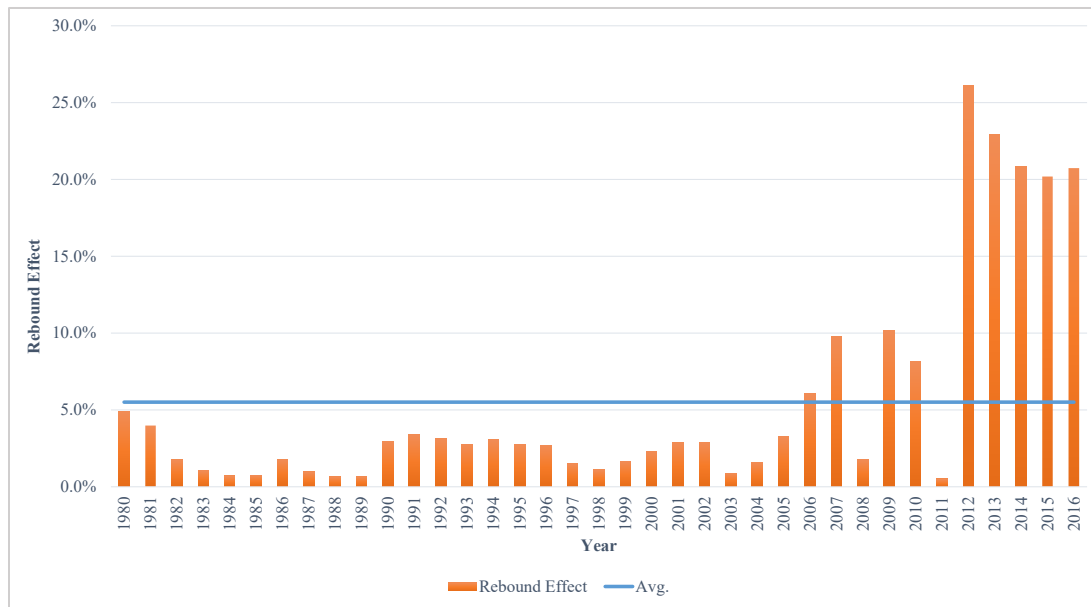


Figure 5: Annual Rebound Effect of the US Road Freight Transport from 1980 to 2016

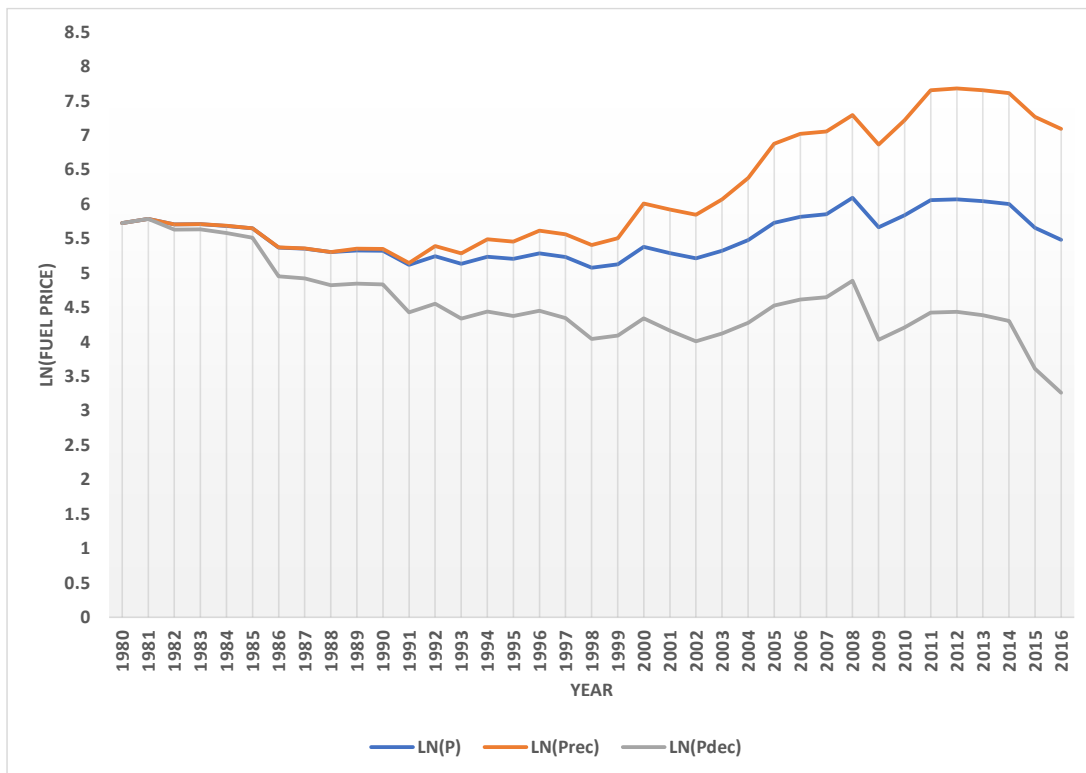


Figure 6: Asymmetric Fuel Price Decomposition

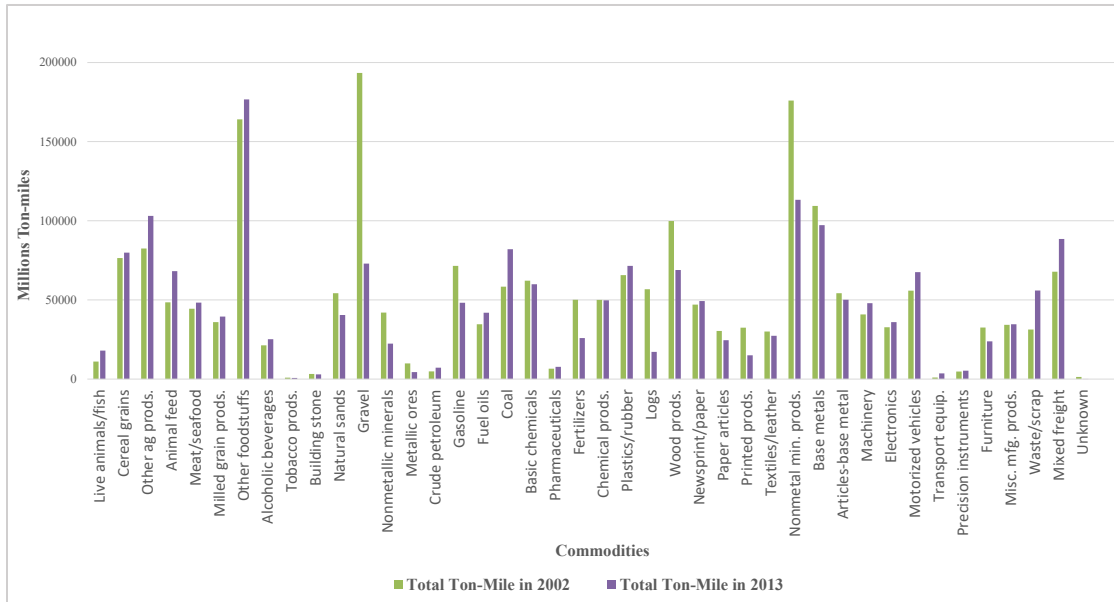


Figure 7: Commodity Transported by US Road Freight in 2002 and 2013 (ORNL, 2019)

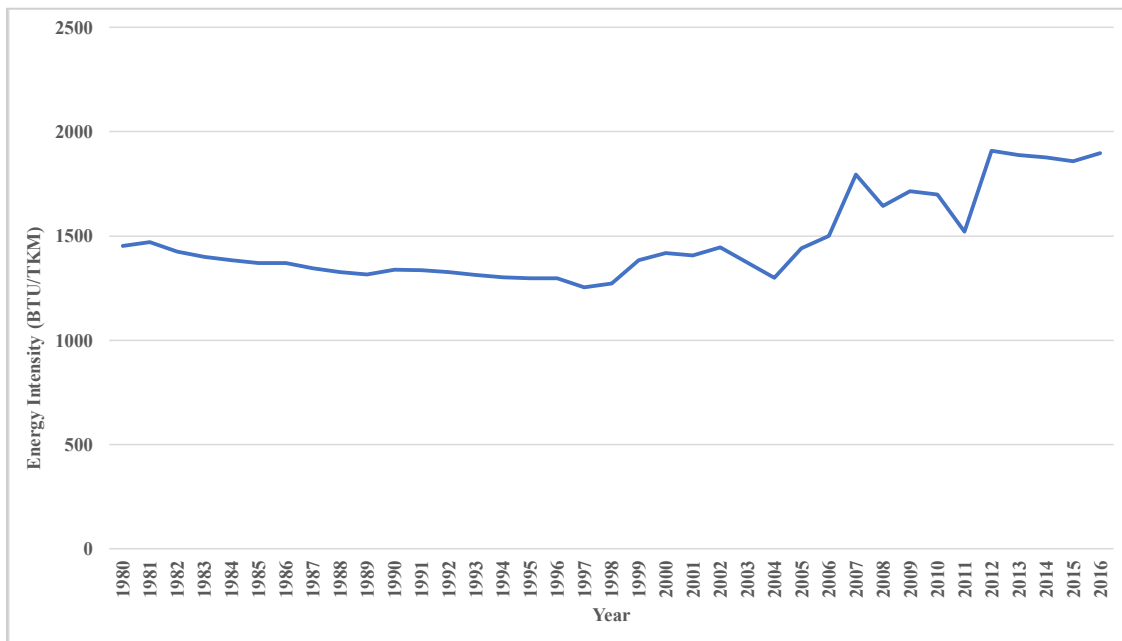


Figure 8: Energy Intensity (EI) of the US Road Freight Transport from 1980 to 2016 (BTS, 2018b; ORNL, 2019)

Table 12: Studies Related to the Energy Efficiency (EE) & Rebound Effect (RE)

Articles	Estimated models	Used Variables*	Findings
Ruzzenenti and Basosi (2017)**	Multiple linear regression	Tonne kilometers (Tkm), GDP, fuel price	RE: -146% to -74%
Llorca and Jamasb (2017)**	Modified Stochastic frontier analysis (SFA)	Energy consumption, GDP, fuel price, stock of trucks, stock of light vehicles, rail goods traffic, road freight transport	RE: 0 to 7.9%
Matos and Silva (2011)**	log-log econometric model	Tonne kilometers (Tkm), Energy cost per Tkm, GDP, fuel price	RE: 24.1%
Sorrell and Stapleton (2018)**	Static and dynamic multiple linear regression models	GDP, manufacturing share of GDP, fuel efficiency, fuel price, fuel cost of Tkm, Regulation and deregulation dummies	RE: 49%
Small and Dender (2007)	Log-log econometric model	Vehicle mile traveled, fuel cost, new vehicle price, fuel price, etc.	RE: 4.5% in short-run and 22.5% in long-run
Wang and Lu (2014)**	log-log econometric model	Fuel price, total retail sales of consumer goods, density of traffic	RE: 52% to 84%
Jin and Kim (2019)	Data Envelopment Analysis (DEA)	GDP, Energy consumption, capital stock, labor force	EE: 93% to 99% RE: 1%
Wang et al. (2018)	Logarithmic Mean Divisia Index decomposition model (LMDID)	GDP, capital stock, labor force, energy consumption, value added of specific industry	RE: -42.22% to 990.54%
Zhou and Ang (2008)	Data Envelopment Analysis (DEA)	Labor, capital, energy inputs, GDP, CO2 emissions	EE: 53% to 100%
Orea et al. (2015)	Stochastic frontier analysis (SFA)	Energy consumption, Energy price, real income, energy efficiency	EE: 83.1% to 97.7% RE: 56% to 79%

Notes:

* The first variable of the “Used Variables” column denotes the dependent variable except for the DEA model, as DEA is non-parametric.

** This article estimated the energy efficiency/ rebound effect for road freight transport.

Table 13: Descriptive Statistics of the Variables

Variables for Static & Dynamic Models	Mean	Std. Dev.	Min	Max
TKM (Millions)	2948606	620796	1.80E+06	4.00E+06
GDP per capita (\$)	34050.3	13799.3	12574.8	57904.2
Fuel cost (\$ per Tkm)	0.03235	0.01442	0.01637	0.06632
Manufacturing Share of GDP	0.43276	0.09759	0.28558	0.67091
Year2012 dummy	0.10811	0.3148	0	1
ULSD dummy	0.2973	0.46337	0	1
Instrumental Variables to Test Endogeneity Issue for GDP				
Fixed Assets (\$Billions)	28906.5	15152.9	9512.5	57296.1
Employees (Thousands)	1436253	203717	1.10E+06	1.70E+06
Unemployment rate	6.37973	1.6071	3.96667	9.70833
Factors of Production for C-D Production Function				
Labor (Thousands)	1319.35	105.902	1104.6	1452.68
New Vehicle Purchases (Thousands)	5661.11	1264.66	3107	7467

Table 14: Diagnostic Tests of the Static and Dynamic Models

Models	H₀: No Heteroscedasticity	H₀: No Endogeneity	H₀: No Serial Correlation
Static 1	Pegan-hall test stat. = 12.13 Chi2(3) P-value = 0.007	2.75 Chi2(1) P-val= 0.09	DW d-statistic: (3, 37) = 0.589
Static 2	Pegan-hall test stat. = 4.14 Chi2(4) P-value = 0.390	0.132 Chi2(1) P-val= 0.718	DW d-statistic: (4, 37) = 0.93
Static 3	chi2(1) = 8.7 Chi2(5) P-value = 0.12	2.10 Chi2(1) P-val= 0.121	DW d-statistic: (5, 37) = 0.76
Static 4	Pegan-hall test stat. = 10.42 Chi2(6) P-value = 0.11	2.68 Chi2(1) P-val= 0.10	DW d-statistic: (6, 37) = 0.76
Dynamic 1	Pegan-hall test stat.= 17.71 Chi2(5) P-value = 0.0014	0.010 Chi2(1) P-val= 0.922	DW h-statistic: -0.366 P-value = 0.099
Dynamic 2	Pegan-hall test stat. = 6.88 Chi2(6) P-value = 0.23	0.402 Chi2(1) P-val= 0.526	DW h-statistic: 0.235 P-value= 0.318
Dynamic 3	Pegan-hall test stat.= 9.29 Chi2(7) P-value = 0.16	1.42 Chi2(1) P-val= 0.233	DW h-statistic: -0.155 P-value = 0.543
Dynamic 4	Pegan-hall test stat.= 10.91 Chi2(8) P-value = 0.142	1.32 Chi2(1) P-val= 0.250	DW h-statistic: 0.685 P-value = 0.006

Table 15: Fit Tests of Instrumental Variables

Models	H₀=Under Identification	H₀= No Weak Identification	H₀= No Over Identification
Static 1	LM statistic: 13.59 Chi2(2) P-value= 0.004	Wald F statistic: 2828.59 Avg. maximal IV size: 11.88	Hansen J statistic: 3.22 Chi2(1) P-value= 0.20
Static 2	LM statistic: 16.14 Chi2(2) P-value= 0.001	Wald F statistic: 2454.48 Avg. maximal IV size: 11.88	Hansen J statistic: 4.2 Chi2(1) P-value= 0.10
Static 3	LM statistic: 11.71 Chi2(2) P-value= 0.008	Wald F statistic: 157.95 Avg. maximal IV size: 11.88	Hansen J statistic: 4.36 Chi2(1) P-value= 0.11
Static 4	LM statistic: 12.55 Chi2(2) P-value= 0.006	Wald F statistic: 153.1 Avg. maximal IV size: 11.88	Hansen J statistic: 3.53 Chi2(1) P-value= 0.17
Dynamic 1	LM statistic: 8.43 Chi2(2) P-value= 0.04	Wald F statistic: 345.84 Avg. maximal IV size: 11.88	Hansen J statistic: 2.82 Chi2(1) P-value= 0.24
Dynamic 2	LM statistic: 8.64 Chi2(2) P-value= 0.04	Wald F statistic: 82.91 Avg. maximal IV size: 11.88	Hansen J statistic: 3.54 Chi2(1) P-value= 0.17
Dynamic 3	LM statistic: 6.82 Chi2(2) P-value= 0.05	Wald F statistic: 115.56 Avg. maximal IV size: 11.88	Hansen J statistic: 0.61 Chi2(1) P-value= 0.434
Dynamic 4	LM statistic: 31.75 Chi2(2) P-value= 0.000	Wald F statistic: 76.43 Avg. maximal IV size: 11.88	Hansen J statistic: 0.05 Chi2(1) P-value= 0.823

Table 16: Parameter Estimates of the Static Models

Variables	Static 1	Static 2	Static 3	Static 4
ln (GDP)	0.525*** (0.0374)	0.584*** (0.019)	0.783*** (0.040)	0.750*** (0.055)
ln (fuel cost)	-0.144*** (0.0419)	-0.064*** (0.023)	-0.121*** (0.0115)	-0.080** (0.028)
ln (manufacturing share)	-	-	0.374*** (0.071)	0.307*** (0.086)
Year2012 dummy	-	-0.231*** (0.020)	-0.222*** (0.009)	-0.223*** (0.013)
ULSD dummy	-	-	-	-0.035 (0.028)
Rebound Effect		6.4%	12.1%	8%

Note: Percentage impact of the dummy variable (D) is estimated by: $100*[\exp(D) - 1]$. *** & ** denote 1% & 5% significance level. The numbers in bracket indicate the standard error.

Table 17: Parameter Estimates of the Dynamic Models

Variables	Dynamic 1	Dynamic 2	Dynamic 3	Dynamic 4
ln (GDP)	0.122 (0.086)	0.432*** (0.096)	0.619*** (0.127)	0.649*** (0.078)
ln (fuel cost)	-0.058 (0.037)	-0.055*** (0.015)	-0.079*** (0.016)	-0.051** (0.023)
Lag (Tkm)	0.740*** (0.147)	0.271* (0.157)	0.225 (0.149)	0.186** (0.093)
ln (manufacturing share)	--	--	0.312*** (0.105)	0.286*** (0.086)
Year2012 dummy	--	-0.180*** (0.039)	-0.183*** (0.041)	-0.188*** (0.024)
ULSD dummy	--	--	--	-0.042 (0.026)
Rebound effect		7.6%		6.3%

Note: Percentage impact of the dummy variable (D) is estimated by $100*[\exp(D) - 1]$. *** & ** denote 1% & 5% significance level. The numbers in bracket indicate the standard error.

Table 18: The Rebound Effects Under Asymmetric Price Response

	Original Fuel Price Estimates	Average Rebound Effect	Recovery Fuel Price Estimates	Average Rebound Effect	Decrease Fuel Price Estimates	Average Rebound Effect
Static 1	-0.144**		-0.078***		-0.109***	
Static 2	-0.064***	8.8%	-0.070***	7.30% (17% decrease)	-0.048	9.5% (8% increase)
Static 3	-0.121***		-0.090***		-0.130***	
Static 4	-0.08**		-0.060***		-0.059***	
Dynamic 1	-0.223		-0.144**		-0.161	
Dynamic 2	-0.076***	6.90%	-0.050***	5% (27.5% decrease)	-0.055**	7.10% (2.9% increase)
Dynamic 3	-0.102		-0.063***		-0.099***	
Dynamic 4	-0.063**		-0.038*		-0.060***	

Notes: ***, ** & * denote 1%, 5%, & 10% significance level. # One term lag is used for the dynamic models.

CHAPTER IV

CONCLUSION

Transportation builds the economy by moving people and goods. It also has resulted in increased energy use, traffic congestion, pollutions, and land-use change. US airports play a vital role in the nation's economic growth. The deregulation of US commercial aviation in the 1970s increased the growth and efficiency of US airports. Currently, however, many airports have outdated and crowded (i.e., operating beyond capacity) facilities resulting in frequent flight delays and increased local air pollution.

The US road freight sector also plays an important role in building the nation's economy as it continues to expand over the past few decades. The surge of eCommerce driven by the increasing ease of online shopping has in part induced this growth. However, energy consumption and related GHG emissions have increased with the latter surpassing GHG emissions for the electric power sector in 2016. Therefore, it is crucial to have an efficient system to reduce energy use, ease traffic congestion, reduce pollution and save costs.

The overall aim of this study is to determine the efficiency of two major transportation services, airports and road freight, in the United States. The operational efficiency of the US airports is analyzed by considering local air pollutions and flight delays as undesirable outputs, and related carryover activities (such as debt, expenditure, and use capital) to account for the linkage of consecutive periods. Further investigation examines the factors that could explain the variation among airport efficiency.

The findings from our airport study reveal that the inclusion of carryovers and undesirable outputs in the airport efficiency calculation is crucial. We found that medium

airports perform better with the undesirable outputs/ carryovers' inclusion. Some inefficient airports have improved their operations to reach the efficient frontier over time, while a smaller number remained inefficient given the years. We also found that GDP, education attainment, fleet size, the international share of flights all have a positive impact on airport efficiency, whereas, population density and airport hub size have a negative impact on airport efficiency.

We also analyze the rebound effect generated from the energy efficiency improvement in the US road freight transport including under asymmetric energy price responses. Our results suggest that the rebound effect exists in US road freight transport and that the effect has increased in recent years. We also found that the rebound effect increases with decreases in energy price and decreases with energy price increases.

While being vitally important to economic well-being, the transportation sector is also a major source of energy consumption and a major polluter. Hence, evaluating, managing, and planning transportation is very important. Efficiency analysis can be used to assess performance and identify advantages and disadvantages for improving the services. Our overall efficiency study may help the government and academia to further their understanding of the potentials for improving the efficiency of US transportation services and mitigating associated negative externalities. Our airport study provides a clear understanding of what key factors affect airport efficiency in the US that could potentially assist policy makers. For example, airport managers may increase the number of large aircraft by reducing the number of small aircraft, especially for international flights, then fleet size (number of seats per LTO) would be increased. It may increase the airport's

passenger capacity and eventually improve overall efficiency. Airports need to improve facilities and services to cope with the increased traffic, which may be achieved through a new government investment fund solely dedicated to airport improvement. Airports managers could also pay attention to some managerial controllable measures to improve airport efficiency by outsourcing some operations and increased earning of non-aeronautical revenues. They may also consider forming an airline strategic alliance or partnerships to optimize the overall operations, that eventually can improve airport efficiency.

Our road freight study also has some important policy implications. Policymakers need to design policies not only to minimize the energy use but also to take the rebound effect generated from policies into account to better gauge the impact of related policies. Specific policies like Cap-and-trade schemes can be used to tackle the integrated rebound effect. Besides, Policymakers should also consider welfare gains and losses due to impacts on economic efficiency in designing and implementing policies.

VITA

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