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Measuring Seaport Performance and Congestion in the Republic of Korea

Derrick J. Lohr

MEASURING SEAPORT PERFORMANCE AND CONGESTION IN THE REPUBLIC OF KOREA

THESIS

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Abstract

Industries continue to globalize their supply chains, increasing cargo traffic and creating excessive demand on ports across the globe resulting in port congestion. This increased congestion impacts USTRANSCOM's cargo movement operations which compete for use of the same port resources. While the DoD has organic transportation capabilities, most of the cargo is moved via civilian sealift. It is necessary to understand civilian port operations, identify port-specific excess capacity, and exploit it to avoid congestion at other ports. The purpose of this study is to evaluate operational factors to include unloading and loading capacity, warehouse storage capacity, and shipping yard area and their relationship to containerized and non-containerized cargo throughput. Data Envelopment Analysis (DEA) and linear regression were used to analyze seaports in the Republic of Korea (hereafter referred to as South Korean). This research concludes that although all South Korean ports are not fully efficient due to mixes of cargo types, the port of Pyeongtaek demonstrates significant inefficiencies in containerized cargo throughput. This inefficiency could be exploited to accomplish a shorter port processing time relative to a higher efficiency port such as Busan. The selected operational factors were shown to exercise a varying influence over cargo throughput, dependent on which type of cargo was being processed.

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MEASURING SEAPORT PERFORMANCE AND CONGESTION IN THE REPUBLIC OF KOREA

I. Introduction

Background and Problem Statement

The globalization of many supply chains over the past 20 years has increased in combination with the increased size of container ships, which have collectively driven changes in infrastructure for many ports to facilitate the loading and unloading of these massive ships. This increase in cargo traffic has resulted in congestion at many strategic ports throughout the world that US Transportation Command (USTRANSCOM) utilizes to move Department of Defense (DoD) cargo. The port congestion results in delays of sustainment cargo supporting the warfighter in theater and directly impacts their capability to execute the mission.

Total cargo throughput is the most universal performance metric of a port's performance, and knowledge of non-military cargo activity will allow a better understanding of congestion's impact on the relatively small amount of military cargo. Port processing congestion is the primary cause of shipping delays, and the majority of USTRANSCOM shipments to locations in South Korea are late due to delays. Currently, USTRANSCOM primarily utilizes the Port of Busan for cargo either originating from or shipping to South Korea. Busan is the largest port in South Korea and ranks sixth in the world for twenty-foot equivalent unit (TEU) throughput with about 27 million TEUs in 2018 (WSC). Busan handles nearly 75 percent of the container throughput in South Korea (Busan Port Authority, 2019). There are several smaller container ports located on the Korean peninsula that could be utilized if congestion at Busan was forecasted in enough time to allow a change in the shipping route of cargo. Currently, USTRANSCOM does not have a trigger metric for predicting and avoiding shipping container congestion at the Port of Busan or any other port in South Korea.

Purpose Statement

The primary purpose of this study is measure port efficiency and determine slacks and shortages so that USTRANSCOM can identify alternative ports to use to in order to avoid port congestion in South Korea. This study focuses on five variables: Unloading Capacity (Tons), Warehouse Storage Capacity (Sq Meters), Yard Storage Capacity (Sq Meters), Non-container throughput (Tons), and Container Throughput (TEUs). These variables were analyzed regarding their impact on port efficiency at each of the four major ports of South Korea. Each of these variables was then evaluated based on their contribution to the overall port efficiency and how efficiently the resources were utilized. Data Envelopment Analysis (DEA) was used to identify and evaluate the variables critical to high port efficiency. Ports that are identified as having high efficiency utilize their resources to the fullest and are therefore congested. Lower port efficiency measures would imply underutilization of resources and therefore have excess throughput capacity. If there is significant excess capacity, it could imply that the port is not congested, and shipments would be processed without delay.

Research Questions

This study tries to answer the following questions:

- Which factors are useful in measuring a seaport's efficiency?
- Which seaports are efficient or inefficient?
- Is there a port with desired inefficiencies that could be exploited to avoid congestion at other ports?

Research Assumption

Depending on predicted congestion, indicated by high efficiency at South Korea's primary port, a port with lower efficiency may provide a shorter processing time of containerized cargo resulting in a quicker delivery to customers. If this assumption is correct, the smart application of the tools/principles in this research could potentially save USTRANSCOM from shipment delays that increase cost and degrade timely support to the theater commander.

Research Focus

Due to the complexity of analyzing many nodes and potential routes, this research will focus its analysis primarily on cargo throughput of South Korea's four largest ports which account for 95percent of the cargo throughput of the country (Busan Port Authority, 2019). Busan is the largest of South Korea's ports and accounts for 75percent of the country's container throughput (Busan Port Authority, 2019). Currently USTRANSCOM utilizes the primarily uses the port of Busan for containerized and non-containerized cargo. The smaller three ports of Incheon, Gwangyang, and Pyeongtaek make up about 20percent of total container throughput (Busan Port Authority, 2019).

Methodology

The methodology used to analyze the data in this research includes five unique DEA models: Charnes-Cooper-Rhodes (CCR) model, Bankers-Charnes-Cooper (BCC) model, slack-based measure of efficiency (SBM) model, Systems model, and a bilateral model. Linear regression was then used to determine the relational strength among the five variables in each model and the resulting efficiency score.

Limitations

The five variables used in this study have a proven history of use regarding port efficiency, as will be discussed in the following chapter, but some are summations of many smaller variables and possibly miss some smaller relationships that exist in the components. The Multicollinearity between the input and output variables prevents them from being used in a single regression model. Therefore, the two regression models can be analyzed independently, but cannot be used to compare.

II. Literature Review

Chapter Overview

This chapter will provide fundamental knowledge used to support which input and output variables are effective in calculating the efficient use of resources in port operations. This chapter begins by explaining efficiency and its critical role in port operations. This chapter will then cover a brief history of DEA's uses in calculating port efficiency, then focus specifically on DEA measuring port efficiency in the East Asia region.

Measuring and tracking port efficiency in East Asia ports has become paramount as more supply chains globalize to take advantage of lower labor and material cost in the region. The increase in container traffic has induced additional congestion in ports and is only expected to increase in coming years. This congestion impacts every user of the port, regardless of the volume of their shipments. It is necessary to identify and understand which variables contribute to port efficiency, and, in turn indicate excess capacity or shortages. This excess capacity or shortage could be utilized to avoid congestion. No previous studies focused analysis on the impact of South Korean port congestion on USTRANSCOM cargo and the implications of utilizing a port with excess capacity or throughput shortages to avoid congestion.

Port Efficiency

Port efficiency is an important indicator of port performance; more efficient ports lower transportation costs and facilitate import and exports of a country (Merk, 2012). Port efficiency also contributes to a nation's ability to trade globally and compete in high-end global conflicts, the latter of which require a high volume of sustainment that cannot be moved efficiently by other means. Efficiency is determined by the ratio of benefits or outputs to capital utilized or inputs. Military cargo makes up a small portion of throughput in any given seaport, so it is critical to understand the non-military cargo activities that impact the network and route selection of military cargo. Once identified and analyzed, the indicators can be used to measure the efficiency of port operations.

History of DEA and Seaport Operations

As originally proposed by Charnes, Cooper, and Rhodes (CCR, 1978), DEA can be used to measure the efficiency of Decision-Making Units (DMU) when a finite number of inputs are known for a given output. In this study, a DMU is an individual port's monthly data including inputs and outputs. There are four basic DEA models used in the following studies: The CCR, the BCC (Banker et al., 1984), the additive model (Charnes et al., (1985), and the multiplicative model (Charnes et al., 1982). The differences between these models arise from factoring for economies of scale, the shape of the efficiency frontier, and how DMUs are projected on the frontier.

A brief summary of each study in this chapter and its significance can be seen on Table 1 and will be discussed further in this chapter.

Table 1. Summary of Literature Review

Sources	Key Concepts	Inputs	Outputs
Roll & Hayuth (1993)	First use of DEA to measure Port Efficiency, 20 ports and used CCR model	Labor, Capital, and Cargo Consistency	Cargo Throughput and Service
Poitras et al. (1996)	23 Australia Ports; used CCR and Additive models	Mix of TEU, Delays, Labor Hours, Berthing Time, Crane hours, Frequency of Ship Calls	TEUs per berth hour and TEU Throughput
Martinez-Budria (1999)	26 Spanish ports, First attempt at time series data	Labor, Depreciation, Expenditures	Cargo Throughput and Revenue
Valentine & Gray (2001)	Privatization of ports. Port performance and ownership –compared groups	Land and Capital	Cargo Throughput
Valentine & Gray (2002)	19 ports in North America and Europe to compare them	Total Berthing Length	Cargo Throughput
Park & De (2004)	Staged approach to DEA model on port efficiency on 11 Korea ports	Berthing Capacity, Cargo-handling Capacity, Marketability	Cargo Throughput, Productivity, Profit
Yeo (2010)	Competitiveness of 61 Asian Terminals	Cargo moving capacity, multi modal access, facilities convenience, Terminal size,	Container Throughput
Cullaine & Wang (2007)	69 European Containers Ports/ CCR and BCC model were used	Terminal length, Terminal Area, Amount of Equipment	Container Throughput
Nguyen et al (2020)	Used Super-efficiency model of CCR and BCC East Asia ports	Berth Length, Number of cranes, Total Area	Container Throughput
Kou K, C. (2020)	DEA Vietnam ports	Total terminal area; Terminal Length; Equipment	Cargo Throughput and Ship Calls

The earliest known use of DEA to measure port efficiency was conducted by Roll and Hayuth (1993). They utilized the CCR model which focused on the constant returns to scale and provided efficiency scores for the 20 ports in the study. Each port was an individual DMU. They chose labor, capital, and cargo consistency as inputs and both cargo throughput and service as outputs. This first study was mostly theoretical, and dummy variables were used. However, it was a significant breakthrough for measuring port efficiency with DEA.

Poitras et al. (1996) used DEA to analyze the efficiency of 23 Australian ports. They stated that DEA, while having been used previously to measure ports, was suitable for port application as previous knowledge of relative weights on inputs and outputs played no role in calculating efficiency. This study used both the CCR model and the additive model of DEA. The inputs selected were the cargo mix of twenty-foot and forty-foot containers, average delays, the difference in working time and birthing time, the number of containers lifted per crane hour, and the frequency of ship calls. The outputs were TEUs per berth hours, and the total number of containers handled per year. They concluded that DEA had been successfully applied to measure port efficiency and that the results of DEA strongly depended on the model used and which inputs and outputs were selected. This study's major contribution is that it was a proof of concept regarding DEA and measuring port efficiency.

Martinez-Burdia et al. (1999) used DEA to measure the efficiency of 26 Spanish ports using operational data from 1993-97. This study was significant because it was the earliest attempted use of time-series data while acknowledging the differences in ports regarding cargo specialization and size. Each of the 26 ports had five DMUs and was placed in three categories based on complexity. Complexity was determined by range of cargo operations and the size of the port. The complexity of several ports had changed during the years of observation, so DMU's for a given port could be spread between the other two groups. The time-series data provided three inputs and two outputs for DEA. The inputs were labor, depreciation charges, and miscellaneous expenditures. The outputs were total cargo throughput and revenue obtained from port operations. Their study concluded that more complex port structures tended to have a positive efficiency trend whereas less complex ports tended to have a negative trend of efficiency.

Valentine and Gray (2001) used DEA to determine if ownership, private vs public, and port performance were related in 21 container ports. The ports were further sorted under three ownership models and three organizational models of ports for comparison. They used capital and land as inputs and throughput as an output, analyzing the relationships with cluster analysis alongside DEA. The study concluded that DEA could successfully compare different groups and that a simple organizational structure seems to be more efficient, whereas ownership did not seem to be a significant factor. This study has been highlighted in arguments to privatize port operations, noting it was the first to analyze the idea for the industry. Valentine and Gray (2020) also performed another study that applied DEA to 19 ports in North America and Europe. The objective was to compare the ports and further the findings of their previous studies. The inputs were changed to berth length and container ship berth length while the output remained cargo throughput. The study concluded that there might be a relationship, but it was not significant on port performance.

Finally, Park and De (2004) used DEA to perform a four-stage model on port efficiency measurement of 11 South Korean ports. They argued that previous studies had a higher output of generalized efficiency and needed to be more specific to provide a clearer picture of sources of inefficiency. They divided the efficiency into four stages, with inputs and outputs tied to each stage providing efficiency levels at each stage. The goal of the study was to highlight areas of inefficiency for each port in each of the four stages. This study was the first to use DEA for a staged approach.

DEA and East Asian Seaports

The previously discussed studies established DEA as a legitimate tool in analyzing the efficiency of ports given known inputs and outputs. This study will now further explore studies that implemented DEA in East Asian seaports to provide additional context to this research.

In Yeo (2010), the primary focus was calculating the competitiveness of the 61 largest Asian container terminals. Yeo (2010) identified terminal facilities and service levels to be positively associated with overall port performance and analyzed over a dozen qualitative and quantitative variables including operating capacity, electronic document handling capacity, facilities convenience, and multi-modal access. The study found that multiple qualitative and quantitative variables play a significant role in terminal performance efficacy. Terminals with larger terminal facilities were positively associated with high efficiency, which implies that larger terminals with more throughput capacity are more competitive in East Asia. The largest issue identified was that low service level, arising from slow throughput and delays, severely hurt terminal competitiveness and upgrading port services should be paramount.

Cullinane and Wang (2007) focused on improving container port efficiency by identifying the correct inputs and outputs given a port's goals and desire to be competitive in the market. For example, if a port's goal was to make a profit, it might utilize cheap equipment and focus on maximizing profits in the short run. If a port wanted to focus on throughput competitiveness, it was more likely to invest in top-of-the-line equipment and facilities. Throughput was identified as the most widely accepted indicator of port performance and was used as the output variable for DEA. The study concluded that the production process had the most waste that impacted overall efficiency due to poor returns to scale on multiple outputs. Which was useful for making decisions regarding production scale.

Nguyen et al. (2020) analyzed the efficiency of the top ten East Asia shipping container ports, focusing on competition and the market concentration of each port. Historically, the Port of Singapore captured a large section of the market due to location and lack of other competitive ports; however, with the globalization of many markets, many new competitive ports had been built. Market concentration was established using the Herfindahl Index (HHI), Gini Coefficient, and shift-share analysis from 2007-2017. This study applied a super-efficiency DEA model to analyze the association between shift effects and port efficiency. Ports had to maintain a competitive edge through superior operation and optimal efficiency (Nguyen et al., 2020). The results of the study showed that Singapore was still efficient, but only one port was efficient and gaining market share. The other ports gaining market share were inefficient.

Kou et al. (2020) integrated DEA and a forecasting model to measure the efficiency of 53 Vietnamese ports and predicted the future performance of those ports. The inputs used were terminal area, terminal length, and equipment with the outputs of throughput and vessel calls. The study used output-oriented CCR and BCC models and analyzed the return to scales of the Vietnamese ports. The study found that most ports were inefficient due to low pure technical scores, there was a major excess of inputs to outputs in 55 percent of the ports, and that the forecast provided was reliable. The forecasted performance results could aid policymakers regarding production decisions, competitive strategies, and future investments.

Summary

Efficiency and competition have been studied in various ways through a different lens of multiple inputs, outputs, and DEA models. Data envelopment analysis has an established record for analyzing efficiency in seaports and is suitable for use in the focus of this research. There is very little literature in current existence that discusses optimizing trade or shipping routes given periods of peak port operating efficiency. A port that is working at peak efficiency is fully utilizing inputs and does not have an excess capacity which will result in congestion. If analyzed effectively, congested ports could be avoided allowing for shorter shipping times by utilizing different ports that are less efficient due to excess capacity to move shipping containers or have a shortage of container throughput.

III. Methodology

Chapter Overview

The purpose of this chapter is to discuss the two methods consisting of five different DEA models that will be used to calculate relative efficiency between ports and the linear regression that will be used to assess the significance of variables chosen to calculate the efficiency. The DEA models will calculate different efficiency scores based on the utilization ratios of three inputs and two outputs and then compare the ports given their efficiency. Results will also show port inefficiency that can be targeted, improved, or exploited.

Research Methodology

DEA as an efficiency measure is well known. A major benefit of measuring efficiency with DEA is that it can handle multiple inputs and outputs. As discussed in Chapter II, many inputs and outputs have been used in DEA regarding ports, so they are relevant analytical tools to address the underlying problem herein. This study uses three DEA models to calculate efficiency scores and two additional DEA models to compare the efficiency of each port for the year of operation. Each of these DEA models examines the data differently and from multiple perspectives to provide a relative measure of efficiency for each DMU.

The basic framework of production frontier analysis was proposed by Farrell (1957). Expanding on the framework from Farrell, Charnes et al. (1978) were able to solve the model by using linear programming. This linear programming model became known as the CCR model and was named after the creators, Charnes-Cooper-Rhodes.

The CCR model uses constant returns to scale (CRS) to calculate a technical efficiency (TE) score using known inputs and outputs.

Informing out second DEA modeling approach, Banker-Charnes-Cooper expanded on the CCR model by considering variable returns to scale (VRS) and created the BCC model. The BCC model produces a pure technical efficiency (PTE) score which is a measure of internal efficiencies. These internal efficiencies are within each port's operations and therefore in their control. The TE score from the CCR model divided by the PTE score of the BCC model provides a scale efficiency (SE) score which can be used to determine whether a port is operating at the most efficient production locally. Scale efficiency is indicative of external factors affecting operations. These efficiencies are not entirely in control of the port, such as economic conditions or a global pandemic.

The third DEA model used in this study is the slack-based measure of efficiency (SBM) model. The SBM model helps calculate slack or excess of variables that are not completely efficient. The SBM score can be divided by the total efficiency score to calculate a mixed efficiency score (MIX). The MIX efficiency score determines the "optimal mix" of input or output variables for computing efficiency scores.

The fourth model used in this study is the systems model. The previous three models measure the efficiency of each DMU individually. The systems model can be used to compare the efficiency of DMU's in multiple groups. In this study, the groups will be the ports of Busan, Incheon, Pyeongtaek, and Gwangyang. Each group will be made up of 24 DMUs representing 24 months of data.

The fifth and final model is the bilateral model. The bilateral model can compare the efficiency scores of two groups of DMU's. In this study the two groups of DMUs are months in the year 2018 and 2019. Once the efficiency scores are calculated, the bilateral model will assess whether the two group's efficiency scores are statistically different.

Although this study employs five DEA models, the dual linear programing (DLP) form of the CCR model is presented for understanding the basic mathematics of DEA (Cooper et al., 2007: 43).

$$
\begin{aligned}
&(\text{DLP}) \quad \theta \\
&\text{subject to} \\
&\qquad \theta x_0 - \mathbf{X}\boldsymbol{\lambda} \geq 0 \\
&\qquad \mathbf{Y}\boldsymbol{\lambda} \geq y_0 \\
&\qquad \lambda \geq 0
\end{aligned}
$$

where θ is an efficiency score, ***X*** and ***Y*** represent inputs and outputs for the matrix (X, Y), x and y are observed activities, and **λ** is a non-negative vector.

Data and Variables

A total of 96 DMUs were selected from the four largest ports in South Korea. Each DMU represents one month's data of a port from the year 2018 or 2019. The data was not the most recent available, but it was the most current data not impacted by the global COVID-19 pandemic. The pandemic has likely had a significant impact on port efficiency and has not concluded at the time of this study, so it is excluded. Multiple variables were considered to determine which were suitable for measuring port efficiency. The variables considered were unloading/loading capacity, warehouse storage area, yard area, containerized cargo throughput, and non-containerized cargo throughput.

The first input of the study is unloading and loading capacity is a cumulative measure that accounts for multiple variables such as berthing length, labor, number of cranes, and other cargo handling equipment. Unloading and loading capacity is measured in metric tons. Unloading and loading capacity along with the subcomponents are discussed in the literature review. The monthly unloading and loading capacity for each port is provided by the Korean Statistical Information Service (2021).

The second and third inputs of the study are warehouse storage capacity and yard area, are also provided by the Korean Statistical Information Service. Both variables are measured in square meters. It is cost-effective for a business to rent storage at a port warehouse for long-term use. The cargo is closer to the transit hub and cuts down on unnecessary transportation costs. The warehouse storage area captures the presence of this long-term cargo and its impact on overall throughput. The Yard area represents the entire landside footprint of the port. It captures active terminal storage, chassis pools, empty trailers, empty containers, and transit staging and movement areas.

The two outputs of the study are containerized and non-containerized cargo throughput, measured in TEUs and tons respectfully. Data for both are provided by the Korean Ministry of Oceans and Fisheries (2021). Containerized cargo is normally in the standard 20-foot container that is universally used worldwide. The non-containerized cargo consists of bulk raw materials such as coal, metal, oil or cargo too large to fit into a container. Containerized and non-containerized cargo influence the throughput of each other. It is necessary to measure them separately, as ports do not handle each type of cargo equally and the storage and movement of the two are significantly different. Using the inputs given, DEA can produce an efficiency score for each port on a monthly basis.

This efficiency score will indicate how well each port performed regarding containerized and non-containerized cargo throughput based on the inputs. Table 2 summarizes the descriptive statistics of these variables.

Table 2. Descriptive Statistics for Variables

	Load (Ton)	Warehouse (m^2)	Yard (m^2)	Non-container (Ton)	Container (TEU)
Maximum	354,015.00	2,298,425.00	4,098,828.00	23,782,130.00	1,930,551.50
Minimum	93,425.00	56,879.00	1,998,548.70	1,595,079.00	35,726.25
Average	195,652.63	636,184.50	2,755,162.18	10,237,666.85	584,058.64
Standard Deviation	97,919.29	959,932.56	805,330.23	7,208,198.76	717,716.35
Variable Type	Input	Input	Input	Output	Output

There is large variability in all inputs and outputs due to the size and specialization differences of each of the ports. For example, Busan is a large port specialized in containerized cargo. The smaller three ports move a significant amount of non-containerized cargo alongside container cargo. The significance of a port specialty is further explained in the results. Table 3 shows the correlation between the variables used in this model.

Table 3. Correlation Metrics for Variables

	Load (tons)	Warehouse (m^2)	Yard (m^2)	Non-container (tons)	Container (TEU)
Load					
Warehouse	-0.02				
Yard	-0.17	-0.53			
Non-container	-0.39	0.92	-0.36		
Container (TEU)	0.95	-0.32	-0.04	-0.65	

A strong correlation between the input and the output is desired whereas the correlation between the inputs can raise issues of validity of the variables. More specifically, a strong correlation between the inputs can suggest the inputs are mathematically the same. The strongest correlation between the inputs is between yard area and warehouse area, which is understandable as both are measuring storage capacity even though they are used very differently. The correlation is -0.53 which is moderate correlation, but not severe so both inputs will remain. There is a strong correlation of 0.95 between unloading and loading capacity with container throughput. A second strong correlation of 0.92 exists between non-containerized cargo throughput and warehouse area. This relationship suggests that a port with a larger warehousing capacity also moves more non-containerized cargo. The other inputs and outputs have a moderate correlation except for yard area and container throughput, which has a low correlation of 0.04. This may be a result of the way containers can be stacked while using a limited amount of space or that most containers are downloaded straight onto trailers that leave and do not take up space in the yard.

Linear Regression

Simple and multiple linear regression was applied to determine the degree to which input variable affects containerized and non-containerized cargo throughput in ports. Linear regression was first introduced by Sir Frances Galton in 1885 to determine the relationship between the height of fathers and their sons. He observed that sons did not tend toward their father's height, but "regressed to" the mean height of the population. This result established Galton's "regression toward mediocrity" concept, and with the development of the method of least squares procedures by Carl Friedrich Gauss (Myers, 1990), multiple regression analysis using ordinary least squares procedures has become one of the most common statistical techniques for investigating and modeling relationships among variables (Ethington et al., 2002).

In its most basic model, linear regression is mathematically shown as $y = mx + c$. This equation demonstrates the relationship between the independent variable, x, and the dependent variable, y (Kumari & Yadav, 2018). Linear regression also provides a coefficient of determination, r-squared (R^2), that calculates how much of the variance observed in a dependent variable can be explained by the independent variable. The R^2 will be between 0 and 1. An R^2 close to 1 would indicate a strong linear relationship between the dependent and independent variable while a R^2 closer to 0 indicates a weak relationship. If R^2 is equal to 1, then 100 percent of the change in the dependent variable is explained by the change in the independent variable (Kumari & Yadav, 2018). In this study, multiple linear regression was used to determine the extent that unloading and loading capacity, warehouse area, yard area, container throughput, and non-containerized cargo throughput influenced port efficiency. The strength of the influence was determined using standardized β coefficients.

Summary

This chapter started with the most basic DEA model, CCR, and explained the differences and benefits of each of the four models that build on the original model. Next the sources of the data were discussed along with the variables that will be utilized in this study. Finally, basic linear regression and its utility in assessing influence was discussed.

IV. Results and Discussion

Chapter Overview

The analysis and results section of this thesis will review the outcomes of the data and methods covered in Chapter III. The completion of this analysis will inform the final recommendation regarding best predictors of port congestion, which ports demonstrate excess cargo throughput capacity, and which ports could serve as a viable option to avoid the predicted congestion.

DEA Models and Results

The three output-oriented DEA models (CCR, BCC, and SBM) used in this study calculated how efficiently each of the four ports was fully utilizing resources to achieve cargo throughput. Out of the 96 DMU's, only 6 earned an efficiency score of 1.0. These can be seen in Table 4. This means that, out of the 96 months observed, there were only a few of occasions when a port was fully efficient. The six DMU's that scored 1.0 served as benchmarks or points of reference for other DMUs to pace their adjustments to improve their efficiency. No port was fully efficient across the period of a year, and the 6 DMU's are split between the four ports with each port having a minimum of one and the max of two scores of 1.0 from January 2018 to December 2019.

Table 4. Fully Efficient DMUs

DMUs	BCC-O Score	CCR-O Score	SBM-O-C Score	Scale Efficiency*	MIX efficiency**
Busan_11_18	1.0	1.0	1.0	1.0	1.0
Incheon_12_18	1.0	1.0	1.0	1.0	1.0
Pyeongtaek_03_18	1.0	1.0	1.0	1.0	1.0
Gwangyang_01_18	1.0	1.0	1.0	1.0	1.0
Busan_01_19	1.0	1.0	1.0	1.0	1.0

Gwangyang_10_19	1.0	1.0	1.0	1.0	1.0

*: Scale Efficiency = CCR-O/BCC-O; **: MIX Efficiency = SBM-O-C/CCR-O

Table 5 provides summary data from the DEA models. DMUs are named by following this format: Port Name_MM_YY where MM represents a month, and YY means two digits for the year. The entire results table from the DEA models can be found in the Appendix A.

Table 5. Efficiency Scores by CCR, BBC, and SBM models

Countries	BCC-O Score	CCR-O Score	SBM-O-C Score	Scale Efficiency*	MIX efficiency**
Busan 2018	0.95	0.95	0.88	1.00	0.93
Incheon 2018	0.93	0.92	0.90	0.99	0.97
Pyeongtaek 2018	0.95	0.94	0.78	0.99	0.83
Gwangyang 2018	0.94	0.93	0.84	0.99	0.91
Busan 2019	0.96	0.96	0.89	1.00	0.93
Incheon 2019	0.86	0.86	0.82	0.99	0.95
Pyeongtaek 2019	0.95	0.91	0.67	0.95	0.73
Gwangyang 2019	0.95	0.94	0.86	0.99	0.92
Mean	0.95	0.94	0.86	0.99	0.92

*: Scale Efficiency = CCR-O/BCC-O; **: MIX Efficiency = SBM-O-C/CCR-O

Looking at the average efficiencies for each category of Table 4, SE ranked the highest at 0.99, which suggests that all four of the ports are operating in similar external conditions. The next highest average efficiency is the BCC at 0.95, indicating that collectively the South Korean Ports are internally efficient. Individually, the port of Incheon had multiple months of low BCC scores in 2019 that resulted in it having the lowest average BCC score of 0.86. This suggests that, of the four ports observed, Incheon had the most room for internal operating improvement. The differences between the port's PTE scores will be analyzed in depth by the systems DEA model. The lowest average score between the categories is the SBM score at 0.86 which indicates that there is excess, or slack, capacity not being utilized to accomplish cargo throughput. The lowest individual average SBM scores belong to the Port of Pyeongtaek, which score an average SBM score of 0.78 in 2018 and 0.67 in 2019. Pyeongtaek also had the lowest two average MIX scores, 0.83 and 0.73, indicating that the mix of resources used to obtain cargo throughput was not optimal. Pyeongtaek's average SE score for 2019 is 0.95 which makes it the only port to have an average SE score below 0.99. It is unclear what external factor impacted the scale efficiency.

Since the goal of this study is to find available excess capacity indicated by inefficiency, the lowest score overall should be a good place to start. The mean SBM score is the only score to firmly sit below 0.90. The SBM is a composite score calculated by multiplying the MIX, PTE, and SE scores. The low SBM scores are a result of the low MIX scores. The SE scores on average are very efficient, scoring 0.99, and all but one PTE score is above 0.90. The low MIX scores are indictive of cargo specialty and the port's infrastructure. The Port of Busan is the sixth-largest container port in the world and specializes in container traffic while still moving bulk non-containerized cargo. The Port of Busan annually moves three times the TEUs that the other three ports move collectively in the same period. The ports of Incheon, Pyeongtaek, and Gwangyang move roughly 22 times more non-containerized cargo than Busan does annually. Due to the cargo specialization of the ports, there is an inefficient use of resources to accomplish throughput of the cargo not in focus.

Table 5 provides a more strategic operating view of which areas ports may or may not be properly utilizing resources to achieve port efficiency, Table 6 provides a more tactical look at which inputs and outputs need to increase or decrease in order to become efficient. Table 6 is annual summary data of the complete SBM output-oriented model (SBMOC) which can be found in Appendix B.

Table 6. Summary Projections by the SBMOC Model

Port_Year	Score	(I) Load	(I) Warehouse	(I) Yard	(O) Non-Container	(O) Container
Variable Type		Input	Input	Input	Output	Output
Busan 2018	0.88	-1.41	0	-0.56	29.27	0
Incheon 2018	0.90	0	0	-8.13	0	23.44
Pyeongtaek 2018	0.78	0	0	0	0	62.00
Gwangyang 2018	0.84	0	-10.16	-2.91	0	41.70
Busan 2019	0.89	-0.96	0	-0.38	27.02	0
Incheon 2019	0.82	0	0	-14.32	0.00	47.71
Pyeongtaek 2019	0.67	-0.12	0	0	0.00	119.82
Gwangyang 2019	0.86	0	-8.18	-2.34	0	35.50

The numbers in Table 6 are percentages and relative to one another; as a change in one variable will result in the slack changes across other variables. Since the model used is output-oriented, a negative percentage in an input represents excess capacity and a positive percentage in outputs represents a shortage and a necessary increase to reach maximum efficiency. For example, Busan_01_2018 scored a 0.82 SBM efficiency score. To reach a score of 1.0, the port would need to reduce loading and unloading capacity by 5.14 percent or reduce yard area by 2.05 percent or increase non-container cargo throughput by 43.93 percent.

The slack and shortages shown in Table 5 illustrates how each of the ports is specialized in either non-containerized or containerized cargo. The port of Busan does not have any slack in container cargo while the other three ports do not have any slack in the non-containerized cargo. The goal of this research is to discover which of the ports is inefficient due to excess capacity to move containerized cargo, so we will focus on the three ports with container throughput shortages. The ports of Incheon, Pyeongtaek, and Gwangyang all require significant increases in containerized cargo traffic to become efficient given the resources each port has. The difference between the three ports is that Incheon and Gwangyang have slack in multiple input variables, while Pyeongtaek only has a shortage in the output of container throughput. For Pyeongtaek to reach maximum efficiency, it can only do so by increasing its container throughput. The required increase in monthly throughput is consistently greater than the ports of Gwangyang and Incheon in 2018 and 2019. This shows, that while all three ports have excess capacity to move container cargo, Pyeongtaek has significantly more.

The output-oriented systems models (SYSOC) of DEA provided a direct comparison between each of the ports by comparing the PTE scores from the BCC model. The Systems model was calculated using both constant and variable returns to scale, but the scores were identical. Table 6 provides the summary data from the Systems model.

Table 7: Summary Statistics from SYS-O-C model.

Port	Busan	Incheon	Pyeongtaek	Gwangyang
No. of DMUs	24	24	24	24
Average	0.951	0.957	0.953	0.941
Standard Deviation	0.038	0.052	0.053	0.052
Maximum	1.000	1.000	1.000	1.000
Minimum	0.864	0.765	0.787	0.801

As discussed earlier in the results, the systems model shows that, on average, South Korean ports are internally efficient with each port averaging a PTE score in the mid-90s. Busan has the smallest standard deviation in efficiency scores which shows that it is the most consistent with maintaining internal efficiency.

The Bilateral SBM (Slack-Based Measure of Efficiency) model compares the DMU's by grouping them by year. This model compares the SBM scores between 2018 and 2019 to determine whether the efficiency scores of each year differ in a statistically significantly way using a non-parametric rank sum test. The rank-sum statistics for the SBMC model are in Table 8.

Table 8: Rank Sum Statistics of Bilateral SBMC

2018	2078
2019	2578
Test statistics	-1.832
NormDist	0.033
Significance level	0.0669

The model was calculated with constant and variable returns to scale. The null hypothesis was that the two years have the same distribution of efficiency scores. The model with constant returns to scale resulted in a rejection of the null hypothesis at a significance level of 0.0669. The two years are significantly different with 2018 being significantly more efficient than 2019. In the model with variable returns to scale, there was not significant evidence to reject the null hypothesis.

Linear Regression Analysis

Multivariate linear regression was performed to determine the strength of the relationship between the five variables used in the DEA models and the resulting port efficiency score of each DMU. As discussed in chapter 3, the high correlation between input and output variables, is desirable for DEA analysis, but causes multicollinearity in linear regression. Due to the high variance inflation factor caused by the correlation, the input variables and output variables were measured in separate models. With the two separate models, the highest variable inflation factor is 1.74. The model summary is shown in Table 9.

Table 9: Regression Results

	Variable Type	Model 1	Model 2
Loading and Unloading Capacity	Input	0.414***	
Warehouse Storage Capacity	Input	0.315*	
Yard Area	Input	0.378**	
Non-containerized Cargo Throughput	Output		0.471***
Containerized Cargo Throughput	Output		0.606***
F-Statistics		0.0001	0.0001
Adjusted R^2		0.203	0.200

*: significant at α=.005; **: significant at α=.001; ***: significant at α=.0001

Model 1 consists of the three input variables: loading and unloading capacity, warehouse storage capacity, and yard area as independent variables and the SBM efficiency score as the dependent variable. Model 2 consist of the two output variables, non-containerized and containerized cargo throughput, as independent variables and the SBM efficiency score as the dependent variable. The first number on Table 9 is 0.414 under Model 1 and loading and unloading capacity. This number is a standardized β coefficient, which represents the influence an independent variable has on a dependent variable. A standard

β approaching 1 represents a strong influence on the dependent variable. The asterisk next to the standardized β coefficients represents the variable's level of significance, which the corresponding value can be found below the table. Below the independent variables are the F-statistic which represents the model's overall significance and probability of error. The bottom row of the table is the adjusted R^2, which is the percentage of variation in the dependent variable that is explained by the model. For example, in Model 1, roughly 20 percent of port efficiency scores can be explained by unloading and loading capacity, warehouse storage area, and yard area.

The standard β coefficients of Model 1 show that of the three input variables, loading and unloading capacity has the strongest influence on the efficiency score followed by yard area then warehouse storage capacity. In Model 2, containerized cargo throughput has a much stronger influence on the efficiency score than non-containerized cargo throughput. Both models had similar R^2 and F-statistic values.

Summary

This results and discussion section is structured to allow each method to build on the previous and provide connections between each method and an overall picture of how to port efficiency scores are determined, and which factors have influence on efficiency. The DEA model depicted how efficiently each port utilized its resources to accomplish cargo throughput. Internal operating efficiency and scale efficiency ranked the highest across all four South Korean Ports, while the SBM score had the lowest average score resulting from lower MIX scores. From this observation, we can conclude that a better mix of inputs or outputs would be ideal for increasing the SBM scores.

The projections of the SBM model were leveraged to show relative resource allocation for each port and their cargo throughput. The CCR and BCC models provided a strategic view of port operations and pointed out that inefficiency resulted from low MIX scores and the SBM model showed a clear picture of exactly which resource allocations had slack. The slack found illustrated the existence of excess capacity to move containerized cargo. The systems model grouped and directly compared the four-port and their BCC efficiency scores, which again confirmed that all four ports were internally efficient. The bilateral model compared the DMUs of 2018 and 2019 and concluded that the efficiency scores do not have the same distribution and that 2018 DMUs were more efficient under constant returns to scale.

Following the DEA model, linear regression was used to analyze the relationship between the five model variables and port efficiency. The strongest relationship between inputs variables exists between loading and unloading capacity and port efficiency. The strongest relationship between outputs variables is between container throughput and port efficiency.

V. Conclusions and Future Research

Conclusions of Research

The increasing globalization of supply chains will continue to drive congestion as port infrastructure and capacity to handle the demand lags. The Port of Busan is a major port and handles most container traffic in and out of South Korea. While the easiest option is to ship every container of DoD cargo through the Port of Busan and hopes it is not delayed, the reality is that the smaller, less efficient ports potentially offer shorter processing times, and fewer delays.

Significance of Research

This study uniquely utilized DEA to identify which ports were highly efficient and which had the sought-after inefficiencies, such as a shortage of container throughput, that indicate an excess capacity to move shipping containers, the primary mode of USTRANSCOM cargo in and out of South Korea. Subsequently this study leveraged linear regression to determine which variables had the most influence on overall efficiency of a port to better predict increases and decreases of port efficiency.

Limitations

This thesis has several limitations. The first limitation regards the variables used in measuring efficiency. As discussed in Chapter 2, DEA is very dependent on which variables are selected and used. There are other variables that could be relevant that were not available for this study. The second limitation is that liner schedules were not considered for each individual port. A third limitation is that this study has not consider

USTRANSCOM's ability to change arrival ports once underway or the lead time required to change shipping routes.

Future Research

The first recommendation regards other relevant variables to measure port efficiency. There are many relevant variables that could better calculate relative efficiency scores that were not available for this study. Delays are a concern when cargo is time sensitive and ultimately delays resulting from congestion is a focus of USTRANSCOM. The numbers of delays and the delay durations for each port was not available for this study but could serve as undesired output variables in a DEA model.

The second recommendation is to study the differences in liner schedules for each of the alternative ports. Each of the ports in this study have different transit times from CONUS due to different ports of embarkation, routes, and ship size. It is necessary to further analyze the differences to better understand whether the potential time saved in container port processing time is offset by any increases in transit time to those alternative ports.

The third recommendation for further research is to examine USTRANSCOM's ability to reroute ships or the required lead time needed to change arrival ports to avoid congestion. If the ability to reroute while underway is limited or nonexistent, the research can focus on figuring out how much time is required to change routes to avoid congestion.

Appendix A. DEA Results

DMU	BCC-O Score	CCR-O Score	SBM-O-C Score	Scale Efficiency	MIX efficiency
	0.95	0.95	0.88	1.00	0.93
BS_01_18	0.90	0.90	0.82	1.00	0.91
BS_02_18	0.87	0.87	0.73	1.00	0.85
BS_03_18	0.94	0.94	0.89	1.00	0.94
BS_04_18	0.96	0.96	0.91	1.00	0.95
BS_05_18	0.98	0.98	0.95	1.00	0.97
BS_06_18	0.95	0.95	0.88	1.00	0.92
BS_07_18	0.96	0.96	0.89	1.00	0.93
BS_08_18	0.92	0.92	0.82	1.00	0.89
BS_09_18	0.96	0.96	0.89	1.00	0.93
BS_10_18	0.95	0.95	0.88	1.00	0.92
BS_11_18	1.00	1.00	1.00	1.00	1.00
BS_12_18	0.95	0.95	0.86	1.00	0.91
IC_01_18	0.99	0.98	0.96	0.98	0.98
IC_02_18	0.98	0.93	0.88	0.95	0.95
IC_03_18	0.98	0.96	0.94	0.99	0.98
IC_04_18	0.90	0.90	0.87	1.00	0.97
IC_05_18	0.89	0.89	0.86	1.00	0.97
IC_06_18	0.94	0.94	0.92	1.00	0.98
IC_07_18	0.92	0.92	0.89	1.00	0.97
IC_08_18	0.83	0.83	0.78	1.00	0.94
IC_09_18	0.90	0.90	0.86	1.00	0.96
IC_10_18	0.92	0.92	0.89	1.00	0.97
IC_11_18	0.94	0.93	0.91	1.00	0.98
IC_12_18	1.00	1.00	1.00	1.00	1.00
PT_01_18	0.92	0.92	0.70	1.00	0.76
PT_02_18	0.93	0.93	0.61	1.00	0.66
PT_03_18	1.00	1.00	1.00	1.00	1.00
PT_04_18	0.93	0.92	0.73	0.99	0.79
PT_05_18	0.95	0.94	0.77	0.99	0.83
PT_06_18	0.92	0.92	0.72	1.00	0.78
PT_07_18	0.95	0.91	0.72	0.96	0.79
PT_08_18	0.87	0.87	0.58	1.00	0.68
PT_09_18	1.00	0.99	0.97	0.99	0.97
PT_10_18	0.96	0.95	0.82	0.99	0.86

PT_11_18	1.00	0.94	0.80	0.94	0.85
PT_12_18	1.00	1.00	0.99	1.00	0.99
GY_01_18	1.00	1.00	1.00	1.00	1.00
GY_02_18	0.80	0.77	0.59	0.96	0.76
GY_03_18	0.89	0.88	0.75	0.99	0.85
GY_04_18	0.93	0.92	0.82	0.99	0.89
GY_05_18	0.96	0.95	0.89	0.99	0.93
GY_06_18	0.90	0.89	0.76	0.99	0.86
GY_07_18	0.97	0.97	0.92	1.00	0.95
GY_08_18	0.93	0.92	0.82	0.99	0.90
GY_09_18	0.92	0.91	0.80	0.99	0.88
GY_10_18	1.00	0.99	0.98	0.99	0.99
GY_11_18	0.93	0.92	0.83	0.99	0.90
GY_12_18	1.00	0.99	0.97	0.99	0.98
BS_01_19	1.00	1.00	1.00	1.00	1.00
BS_02_19	0.86	0.86	0.73	1.00	0.85
BS_03_19	0.99	0.99	0.96	1.00	0.98
BS_04_19	0.98	0.98	0.96	1.00	0.97
BS_05_19	0.99	0.99	0.96	1.00	0.97
BS_06_19	0.96	0.96	0.89	1.00	0.93
BS_07_19	0.98	0.98	0.91	1.00	0.93
BS_08_19	0.95	0.95	0.82	1.00	0.87
BS_09_19	0.88	0.88	0.75	1.00	0.85
BS_10_19	0.98	0.98	0.92	1.00	0.94
BS_11_19	0.95	0.95	0.85	1.00	0.90
BS_12_19	0.97	0.97	0.92	1.00	0.95
IC_01_19	1.00	0.98	0.98	0.98	0.99
IC_02_19	0.77	0.74	0.64	0.96	0.87
IC_03_19	0.87	0.87	0.83	1.00	0.95
IC_04_19	0.88	0.87	0.84	1.00	0.96
IC_05_19	0.82	0.82	0.79	1.00	0.96
IC_06_19	0.83	0.83	0.79	1.00	0.96
IC_07_19	0.85	0.85	0.82	1.00	0.96
IC_08_19	0.80	0.80	0.75	1.00	0.94
IC_09_19	0.77	0.77	0.73	1.00	0.95
IC_10_19	0.84	0.83	0.80	1.00	0.95
IC_11_19	0.90	0.90	0.87	1.00	0.97
IC_12_19	0.99	0.98	0.97	0.99	0.99
PT_01_19	1.00	0.98	0.81	0.98	0.83
PT_02_19	0.79	0.79	0.33	1.00	0.41

PT_03_19	0.93	0.79	0.50	0.85	0.63
PT_04_19	0.97	0.91	0.68	0.94	0.75
PT_05_19	0.99	0.97	0.79	0.98	0.82
PT_06_19	0.95	0.91	0.67	0.96	0.73
PT_07_19	0.98	0.88	0.64	0.90	0.72
PT_08_19	1.00	0.99	0.88	0.99	0.89
PT_09_19	0.86	0.83	0.51	0.96	0.61
PT_10_19	1.00	0.94	0.75	0.94	0.80
PT_11_19	0.99	0.96	0.77	0.97	0.81
PT_12_19	0.99	0.94	0.74	0.94	0.79
GY_01_19	0.99	0.99	0.98	1.00	0.99
GY_02_19	0.87	0.82	0.66	0.94	0.81
GY_03_19	1.00	0.98	0.95	0.98	0.97
GY_04_19	0.97	0.96	0.91	0.99	0.95
GY_05_19	0.96	0.95	0.89	0.99	0.94
GY_06_19	0.95	0.94	0.87	0.99	0.92
GY_07_19	0.96	0.95	0.88	1.00	0.93
GY_08_19	0.95	0.95	0.88	1.00	0.92
GY_09_19	0.87	0.87	0.70	1.00	0.81
GY_10_19	1.00	1.00	1.00	1.00	1.00
GY_11_19	0.86	0.85	0.70	0.99	0.82
GY_12_19	0.98	0.98	0.94	1.00	0.96

Appendix B. Projections by the SBMOC Model

(DMUs) Ports mm_yr	Score	(I) Load	(I) Warehouse	(I) Yard	(O) Non-Container	(O) Container
BS_01_18	0.8199	-5.136	0.000	-2.047	43.932	0.000
BS_02_18	0.7346	-6.471	0.000	-2.579	72.255	0.000
BS_03_18	0.8887	-2.447	0.000	-0.975	25.040	0.000
BS_04_18	0.9068	-0.840	0.000	-0.335	20.548	0.000
BS_05_18	0.9536	0.000	0.000	0.000	9.739	0.000
BS_06_18	0.8825	0.000	0.000	0.000	26.641	0.000
BS_07_18	0.8935	0.000	0.000	0.000	23.836	0.000
BS_08_18	0.8203	-1.983	0.000	-0.790	43.818	0.000
BS_09_18	0.8881	0.000	0.000	0.000	25.203	0.000
BS_10_18	0.8754	-0.009	0.000	-0.003	28.474	0.000
BS_11_18	1.0000	0.000	0.000	0.000	0.000	0.000
BS_12_18	0.8630	0.000	0.000	0.000	31.747	0.000
IC_01_18	0.9609	0.000	0.000	-0.512	0.000	8.138
IC_02_18	0.8827	0.000	0.000	-0.036	0.000	26.573
IC_03_18	0.9413	0.000	0.000	-0.554	0.000	12.467
IC_04_18	0.8662	0.000	0.000	-13.054	0.000	30.888
IC_05_18	0.8611	0.000	0.000	-15.288	0.000	32.276
IC_06_18	0.9234	0.000	0.000	-7.954	0.000	16.589
IC_07_18	0.8927	0.000	0.000	-9.229	0.000	24.052
IC_08_18	0.7832	0.000	0.000	-18.372	0.000	55.35
IC_09_18	0.8611	0.000	0.000	-11.621	0.000	32.256
IC_10_18	0.8944	0.000	0.000	-11.295	0.000	23.607
IC_11_18	0.9131	0.000	0.000	-9.689	0.000	19.029
IC_12_18	1.0000	0.000	0.000	0.000	0.000	0.000
PT_01_18	0.7045	0.000	0.000	0.000	0.000	83.879
PT_02_18	0.6135	0.000	0.000	0.000	0.000	126.011
PT_03_18	1.0000	0.000	0.000	0.000	0.000	0.000
PT_04_18	0.7278	0.000	0.000	0.000	0.000	74.816
PT_05_18	0.7730	0.000	0.000	0.000	0.000	58.738
PT_06_18	0.7203	0.000	0.000	0.000	0.000	77.663
PT_07_18	0.7235	0.000	0.000	0.000	0.000	76.453
PT_08_18	0.5846	0.000	0.000	0.000	0.000	142.137
PT_09_18	0.9669	0.000	0.000	0.000	0.000	6.854
PT_10_18	0.8183	0.000	0.000	0.000	0.000	44.404

PT_11_18	0.7974	0.000	0.000	0.000	0.000	50.83
PT_12_18	0.9892	0.000	0.000	0.000	0.000	2.178
GY_01_18	1.0000	0.000	0.000	0.000	0.000	0.000
GY_02_18	0.5860	0.000	-27.286	-7.823	0.000	141.298
GY_03_18	0.7515	0.000	-14.754	-4.23	0.000	66.122
GY_04_18	0.8226	0.000	-9.516	-2.728	0.000	43.126
GY_05_18	0.8907	0.000	-6.866	-1.969	0.000	24.540
GY_06_18	0.7613	0.000	-14.829	-4.252	0.000	62.697
GY_07_18	0.9163	0.000	-4.756	-1.364	0.000	18.277
GY_08_18	0.8239	0.000	-11.860	-3.400	0.000	42.743
GY_09_18	0.8007	0.000	-12.920	-3.704	0.000	49.768
GY_10_18	0.9776	0.000	-3.188	-0.914	0.000	4.580
GY_11_18	0.8269	0.000	-11.160	-3.200	0.000	41.882
GY_12_18	0.9741	0.000	-4.750	-1.362	0.000	5.320
BS_01_19	1.0000	0.000	0.000	0.000	0.000	0.000
BS_02_19	0.7319	-6.733	0.000	-2.683	73.264	0.000
BS_03_19	0.9649	0.000	0.000	0.000	7.287	0.000
BS_04_19	0.9588	0.000	0.000	0.000	8.588	0.000
BS_05_19	0.9591	0.000	0.000	0.000	8.528	0.000
BS_06_19	0.8863	0.000	0.000	0.000	25.655	0.000
BS_07_19	0.9091	0.000	0.000	0.000	20.008	0.000
BS_08_19	0.8246	0.000	0.000	0.000	42.55	0.000
BS_09_19	0.7488	-4.801	0.000	-1.913	67.079	0.000
BS_10_19	0.9190	0.000	0.000	0.000	17.629	0.000
BS_11_19	0.8474	0.000	0.000	0.000	36.013	0.000
BS_12_19	0.9190	0.000	0.000	0.000	17.632	0.000
IC_01_19	0.9767	0.000	0.000	-0.524	0.000	4.772
IC_02_19	0.6386	0.000	0.000	-18.954	0.000	113.172
IC_03_19	0.8256	0.000	0.000	-11.513	0.000	42.243
IC_04_19	0.8433	0.000	0.000	-14.026	0.000	37.175
IC_05_19	0.7879	0.000	0.000	-20.652	0.000	53.855
IC_06_19	0.7948	0.000	0.000	-18.472	0.000	51.622
IC_07_19	0.8157	0.000	0.000	-15.435	0.000	45.186
IC_08_19	0.7526	0.000	0.000	-20.225	0.000	65.761
IC_09_19	0.7321	0.000	0.000	-25.064	0.000	73.173
IC_10_19	0.7953	0.000	0.000	-17.792	0.000	51.485
IC_11_19	0.8746	0.000	0.000	-9.020	0.000	28.668
IC_12_19	0.9737	0.000	0.000	-0.211	0.000	5.402
PT_01_19	0.8146	0.000	0.000	0.000	0.000	45.528
PT_02_19	0.3267	0.000	0.000	0.000	0.000	412.245

PT_03_19	0.4988	0.000	0.000	0.000	0.000	200.994
PT_04_19	0.6805	0.000	0.000	0.000	0.000	93.882
PT_05_19	0.7877	0.000	0.000	0.000	0.000	53.919
PT_06_19	0.6654	0.000	0.000	0.000	0.000	100.577
PT_07_19	0.6369	0.000	0.000	0.000	0.000	114.040
PT_08_19	0.8786	-1.414	0.000	0.000	0.000	27.642
PT_09_19	0.5096	0.000	0.000	0.000	0.000	192.444
PT_10_19	0.7506	0.000	0.000	0.000	0.000	66.444
PT_11_19	0.7714	0.000	0.000	0.000	0.000	59.277
PT_12_19	0.7384	0.000	0.000	0.000	0.000	70.847
GY_01_19	0.9787	0.000	-1.036	-0.297	0.000	4.359
GY_02_19	0.6639	0.000	-22.884	-6.561	0.000	101.265
GY_03_19	0.9463	0.000	-6.305	-1.808	0.000	11.355
GY_04_19	0.9117	0.000	-5.355	-1.535	0.000	19.378
GY_05_19	0.8930	0.000	-7.772	-2.228	0.000	24.065
GY_06_19	0.8694	0.000	-8.678	-2.488	0.000	30.057
GY_07_19	0.8819	0.000	-6.110	-1.752	0.000	26.781
GY_08_19	0.8760	0.000	-6.129	-1.757	0.000	28.317
GY_09_19	0.7048	0.000	-13.687	-3.924	0.000	83.760
GY_10_19	1.0000	0.000	0.000	0.000	0.000	0.000
GY_11_19	0.7026	0.000	-17.813	-5.107	0.000	84.652
GY_12_19	0.9432	0.000	-2.332	-0.669	0.000	12.045

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