The New Jersey Economy in Times of Crisis: Inefficiencies in Gross Domestic Product Contributions

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Abstract: This paper examines the economic efficiency of New Jersey's gross domestic product (GDP) via its 21 counties. It employs data envelopment analysis (DEA), a non-parametric statistical procedure that tests whether decision-making units are operating on their efficient frontier, to measure the relative performance of all New Jersey counties before, during, and after the 2008-2010 financial crisis. Evidence suggests the economic inefficiency of New Jersey's counties has diminished in recent years and that their subsidy structures are no longer inferior demonstrated by the fact that State-wide economic efficiency was higher in the post-crisis than the pre-crisis period. It also suggests that the NJEDA and other New Jersey State funding sources' economic investments are the two main sources of the increased efficiencies post-crisis. Therefore, to maximize the State's GDP and in a restrained State budget environment, these two sources of spending need to be increased particularly with respect to real estate projects and new business investment which yield \$3.45 and \$2.78 per dollar invested in the economy, respectively. These increases would add over 20% to New Jersey's GDP; therefore, without these incentives the State's economy could struggle for an extended period of time given the COVID-19 crisis.

Keywords: Economic Efficiency, New Jersey, Data Envelopment Analysis, Gross Domestic Product, Real Estate

I. Introduction

We have only begun to experience the ramifications of COVID-19 with respect to New Jersey real estate markets and the economy as a whole. As some analysts try to project what vacancy rates and valuation losses will be, the reality is that we do not know especially given Governor Murphy's moratorium on evictions. We are currently under a cloud covering the reality of lost cashflow as well as commercial property valuations. The combination of income generated from real estate industries, expenditures related to home purchases, the multiplier of housing related expenditures, and new home construction accounted for 19.8% of the gross domestic product (GDP) for the State of New Jersey in 2019. With much of what entails these industries considered non-essential, the effects will be dramatically negative to New Jersey's GDP in 2020 and beyond. This effect may be even more dramatic given that as of July 2020, New Jersey's seasonally adjusted civilian unemployment rate was 13.8% having fallen from 16.8% in June 2020. Comparable United States were 10.2% in July 2020 down from 14.8% in April. By comparison during the Great Recession (2008-2010) these rates were 9.8% at their height in September 2009. As one can see, New Jersey's unemployment rate is around 35% greater than the national average. When combined with the fact that we live in one of the highest cost of living States in the country, we may be facing one of the worst economic environments in the country moving forward. Furthermore, without the maximization of GDP via the State's most efficient inputs (incentives) New Jersey economic outlook could struggle for an extended period of time.

That being said, the state of uncertainty we are experiencing with respect to New Jersey's real estate industry and economic future began well before 2020. On one side of the equation, Governor Murphy's SALT deduction and BAIT workaround programs were primed to bring investment into the State. This combined with some of the nation's most extensive employee benefits on average, had New Jersey primed for a capital infusion from both primary and secondary markets. On the other side of the equation, we have always faced some of the highest business tax rates in the country, but what is truly concerning was the lack of the New Jersey Economic Development Authority's (NJEDA's) intervention despite their funding availability. It is also concerning that no truly quantitative impact studies have ever been conducted surrounding the NJEDA's billions of dollars of support and funding around the State. What is return per dollars invested in the economy? Now more than ever the State needs smart spending to maximize its GDP. This study focuses on the performance and inefficiencies of the NJEDA and other funding sources between 2001 and 2018.

The financial crisis of 2008-2010 and subsequent recovery provide helpful market variation through which to study economic efficiency using New Jersey's annual GDP. Crisis has historically been a precursor to and reason for efficiency gains, such as was witnessed following the Great Depression. The Great Recession is the best and most recent financial crisis we can use to evaluate declines real estate assets as well as their recovery. Financial distress can compel firms to strategic operational changes such as management turnover (Gilson, 1989), debt restructuring (Ofek, 1993), or cutting capital expenditures and employees (Brown, James, and Ryngaert, 1992).[1] A defining aspect of the liquidity crisis[2] of 2008-2010 was a tightening of the credit markets, which pushed many highly-leveraged assets into financial distress. We now know that such distress led to efficiency gains across the real estate industry. Nicholson and Lohrey's (2020) and Nicholson and Stevens' (2020) use of data envelopment analysis (DEA) demonstrated an increase in

[1] Opler and Titman (1994) state, "[These authors] have noted that financial distress pushes firms to change operating strategies in ways that seem to clearly raise efficiency."

[2] We use the term "liquidity crisis" as defined by Case, Hardin, and Wu (2012).

operational efficiency in the real estate industry following the crisis, which corroborated recent work by Highfield, Shen, and Springer (2019) who used a different technique.

In this study, I employ data envelopment analysis (DEA), which is a non-parametric method that calculates relative efficiency and maps an efficient frontier. The frontier allows for a comparison, from a management perspective, of annual GDP for every county in New Jersey. Unlike other methods, DEA does not compare each county to the average efficiency within the dataset. Instead, it uses the most efficient county(s) as the benchmark and permits identification of the most efficient combination of inputs and outputs (Rouse, 1995). The frontier method is also useful in comparing the efficiency of New Jersey's GDP as a whole. Additionally, DEA allows us to identify the factors which cause inefficiency at both the county and state levels before, during, and after the 2008-2010 liquidity crisis era.

I use datasets from Geolytics Inc., the Bureau of Labor Statistics, New Jersey Consolidated Annual Financial Reports (CAFRs), and the Bureau of Economic Analysis which includes all New Jersey counties operating between 2001 and 2018. Overall, I document an industry low-point for economic efficiency of in 2010 with only 10% of New Jersey counties maximizing GDP. In the post-crisis recovery period efficiency rises back to 76% by 2018. These results hold using various forms of county size measures. The DEA output used is *GDP* while inputs include *NJEDA funding*, *Other New Jersey state funding*, *Labor Force over 15 years of age*, *Gross Capital Formation*, and *Federal Funding*. Although I do not test why GDP efficiency may have improved, I offer a handful of possible explanations. Anecdotal evidence suggests the results might be due to the *NJEDA Funding* and *Other New Jersey State Funding* sources increased efficiencies in identification and investment post-crisis. It is not likely due solely to scale efficiency gains. Therefore, to maximize the State's GDP and in a tight State budget environment, these two sources of funding need to be increased by 25.65% and 49.13%, respectively. These increases would add 22.45% to New Jersey's GDP.

Finally, to address a general time trend, I use a difference-in-difference technique to test for statistically significant differences before and after the financial crisis period. The results confirm that in the pre-crisis (2001-2007) and post-crisis (2011-2016) periods DEA efficiency measures are significantly different for NJEDA, other State funding and Federal funding sources. New Jersey counties as a group appear to operate closer to the efficient frontier after the financial crisis of 2008-2010. This result supports the notion that the crisis and the financial stress it imposed on counties pushed the State towards more efficiency.

II. COVID-19's Impact on Real Estate Assets

While this study occurs pre-COVID, it is important to address its impact of commercial real estate submarkets. Especially since both New Jersey and the United States experienced one of the longest economic recoveries in history prior to the pandemic. Projected US GDP was +2.3% for 2020. The hospitality, multi-family and industrial submarket were in the Expansion phase of the market cycle with declining vacancy rates, high absorption and moderate to high new construction. While office and retail were in the Recovery phase experiencing declining vacancies, low new construction and moderate absorption, but primed to move into Expansion.[3]

II.1 Hospitality Market

After the liquidity crisis, hospitality took the longest to recover, but did eventually returned to its pre-2008 levels. However, this pandemic presents new challenges to cash flows with respect to

[3] Please see Integra Realty Resources 2020

expenses, not just revenues. These include room cleaning, sanitizing, housekeeping and general staff safety. Given the high occupancy turnover, the hospitality industry faces the greatest operational expenses moving forward as well as fixed expenses such as liability insurance.

II.2 Multifamily Market

Prior to COVID-19, the New Jersey mutifamily market was strong, but nearing economic equilibrium and the possibility of moving into the Recession phase. This sector should not see many if any long-term effects from COVID-19, but State and Federal rent relief will be necessary in the short-term to prevent cashflow declines. This is also one of the largest tax revenue generators for both State and local governments which cannot afford a decline in valuations and subsequent tax revenues given already struggling state budgets. The one long-term expense may be the safety of tenancy in common amenities such as fitness centers and pools. This will require more common area that will not generate revenue.

II.3 Office Market

Potentially the most uncertain submarket moving forward, the office market was merging into the mixed asset class more so than ever as a cashflow support services for retail, restaurants and hotels. It will most likely experience the greatest set of challenges with respect to demand while maintaining only slightly higher expenses when compared to other submarkets. The WeWork style development with more employees per square foot had caught on quickly due to its dramatic revenue generation per square foot. Now, social distancing may require larger cubicles harkening back to 1970's and 1980's style settings. Vacancy rate reporting will be less reliable in the short-term as more space is require per employee. The changes in revenue per square should be the most closely monitored metric. Analysts and appraiser also need to keep in mind that the work-at-home trend accelerated during the 2008-2010 financial crisis. What industries will find significant expense savings and only slight productivity losses from the work-at-home trends faced during the lockdown? Will they continue with this workforce model?

II.4 Industrial Market

The industrial submarket has experienced more physical transition in Northern New Jersey than any other asset class over the past 15 years. Developers and property managers have done an excellent job of transitioning former manufacturing facilities into smaller e-commerce logistic and data-storage centers making it the most desired asset class. Industrial assets may benefit from the current crisis given dramatic increases in online spending and data server/storage needs of the work from home industry thus driving asset values up. One must also consider the trend of products manufactured in other countries coming back to the United States for production via federal subsidies.

II.5 Retail Market

Online retail had the opposite effect on retail than it did industrial before COVID-19. These changes are projected to increase in intensity. Online spending has increased by more than 25% since the onset of COVID-19. Expenses will increase and revenues will decline. Malls will need to create new environments and possibly continue their trend towards entertainment such as the American Dream to circumvent the effects of online retail, but this will risky as well since social distancing will create new challenges. Retail will need to be more flexible within the retail spaces themselves by not having as many permanently affixed structures within them. Highest and best uses for large retail centers will have to be re-evaluated. Overall, real estate development has been experiencing some very interesting trends since 2001 with these transitions increasing since the 2008-2010 liquidity crisis. I fully expect the innovation and efficiencies to continue within the industry due to COVID-19. The questions is how shore up these submarkets in the short-term. This paper addresses and answer this question using DEA analysis.

III. Literature Review

Frontier efficiency studies of economic efficiencies often employ one of two techniques: DEA or stochastic frontier models.[4] Bauer (1990) provides an early review of the stochastic frontier literature. With regard to DEA, Charnes, Cooper, and Rhodes' (1978) seminal paper sparked what has become an enormous body of literature using the DEA technique. Emrouznejad and Yang (2018) survey the DEA related literature through 2016 and find 10,300 published journal articles, along with 2,200 other articles published as working papers, book chapters, or conference proceedings. A large portion of the early research examined banking efficiency and operations.[5] As Luo (2003) notes, there were special issues in the 1990's on DEA and benchmarking bank efficiency in *Journal of Econometrics*, J*ournal of Banking and Finance, European Journal of Operational Research* and *Management Science*.[6]

Economic growth has thus been studied using DEA in a variety of different indicators, ranging from gross domestic product (GDP), inflation, and unemployment as the primary variables. Lesser studied variables include consumer price index, access to credit, and business

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[4] I recognize there are other techniques for examining cost efficiency such as the distribution-free approach (DFA) or thick frontier method, but have found no applications of them in the literature.

[5] Please see Sherman and Gold (1985) as an early example of a bank efficiency DEA study.

[6] Please see Berger, Hunter, and Timme (1993), Miller and Noulas (1996), and Seiford and Zhu (1999) to further understand the literature from this period.

cycles. Given that differing selections of observed variables lead to different relative efficiency results that are additionally influenced by the choice of the model itself, the selection of inputs and outputs should reflect the interest of analysts. The model should be selected as the most suitable for the process under consideration, here GDP.

DEA as a tool of macroeconomic analysis were was originated 1994 by Färe et al. who analyzed productivity growth in 17 OECD countries between 1979 and 1988. Initially based on the Malmquist productivity index (MPI) introduced by Caves et al. (1982), the authors demonstrated how to account for productivity changes over time. They GDP as the measure of aggregate output along with capital stock and employment as the aggregate input proxies.

This approach was also used by Rao and Coelli (1998) and Krüger et al. (2000). In the first paper, the output variable is real GDP per capita with the inputs labour and capital per capita while the output for the second is GDP in international 1985 prices while inputs are labor and capital stock. Golany and Thore (1997) extended these calculations to take account of social variables such as education, health, and welfare policy. They used three inputs including ratio of real domestic investment to real GDP, ratio of real government consumption expenditure (net of spending on defense and education to real GDP), and the ratio of public expenditure on education to nominal GDP. Four outputs were used including; growth rate of per capita GDP, ratio of nominal social insurance and welfare payments to nominal GDP, 1 minus infant mortality rate ages 0-1, enrolment ratio for secondary education.

Brockett et al. (1999), expanded the potential benefit of DEA applications while retaining the robust nonparametric nature of the original DEA development. They combined DEA window-based analysis, rank matrix transformation, and Kruskal-Wallis nonparametric analysis of variance test. They then identified intertemporal performance trends using any one of several possible efficiency measures and tested the stability over time of the rank positions of the analyzed units.

As one can see, DEA has been used in the analysis of GDP inefficiency comparison at a macroeconomic levels for more than 25 years. This paper is one of the first to breakdown the data at a county level and State level.

IV. Research Design

There are several issues with traditional efficiency performance measures. First, how does one best choose an appropriate benchmark? Second, how does one identify the most efficient combination of inputs and outputs? And third, how does one interpret each unit's performance when compared with the group's average performance, as is found in standard regression models? The DEA technique addresses each of these issues by calculating relative efficiency on a frontier. Charnes, Cooper and Rhodes' (1978) pioneering DEA work uses non-parametric analysis in combination with linear programming to map the production frontier. This circumvents the need for a theoretical model like the capital asset pricing or arbitrage pricing theory models. Instead, DEA allows us to calculate the relative performance of a county compared to the most efficient counties in a dataset.

DEA also allows for multiple inputs and outputs to be combined using the most efficient combination of inputs that produce a certain output, without the need for specifying the functional relationship between them. It allows for multiple inputs and outputs to be analyzed simultaneously with respect to performance analysis and can handle differing units of measure without the need for an a priori tradeoff between them. This means that DEA constructs an efficient frontier that consists of a linear combination compiled from the perfectly efficient firms within a sample.

Deviations from the efficient frontier represent performance inefficiencies that are a function of the failure to minimize inputs and/or maximize outputs.

In this study, we optimize each New Jersey counties' performance compared to its county peers and subsequently evaluate the performance based on the best performing county(s). The interpretive advantage is that the result provides a percentage that inputs can be reduced (or outputs increased) for each inefficient counties to reach the efficient frontier. Alternatively, the much more common standard regression like ordinary least squares (OLS) would only use one optimization to obtain the average relationship for all counties, and then compare each individual county's performance to the average. The interpretation of such an average is less insightful when considering for operational efficiency. One final advantage of the DEA approach is that it allows identification of the characteristics causing county inefficiencies at both the county and State levels.

The model sets the upper bound at 1 and weights are assigned to input and output factors in a manner that makes the DEA model as efficient as possible. This means a county that is maximizing efficiency has a rating of 1 while a county that is minimally efficient has a rating of 0. Countys with an efficiency rating between 0 and 1 are located within the frontier. We follow the mathematical formula for the fractional programming model found in Anderson et. al. (2004), as shown below:

$$\max \qquad h_0 = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$$

$$\text{s.t.} \qquad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad j = 1, \ldots, n,$$

$$u_r,\ v_i \geq 0, \quad r = 1, \ldots, s, \quad i = 1, \ldots, m,$$

where

u_r = weight attached to output factor r,
v_i = weight attached to input factor i,
y_{rj} = amount of output r by unit j,
x_{ij} = amount of input i of unit j,
S = the number of output factors,
M = the number of input factors,
N = the number of DMUs to be evaluated with respect to each other.

The relative efficiency measure, h_o, of each county observation is calculated by maximizing the ratio of weighted output to weighted inputs subject to the constraint that the ratio of all units in the data set have an upper bound of 1. The model solutions assign weights to the input and output factors making each as efficient as possible. A unit with an efficiency rating of 1 is deemed efficient relative to its peers while a unit with an efficiency rating of less than 1 is deemed inefficient. The Anderson et. al. (2004) model solves for "the relative efficiency of the unit and the weights necessary to obtain that efficiency measure." The model forms an efficient frontier from the units with an efficiency rating of 1 while units with an efficiency rating of less than 1 are located inside this frontier. Therefore, the efficient frontier "envelops" the units that are deemed to be inefficient. In application, as Boussofiane, Dyson, and Thanassoulis (1991) note, the fractional DEA program is converted to a linear form so one can apply linear programming methods.

With respect to Pareto efficiency, one other advantage of the technique is that efficiency can be defined by either output maximization or input minimization. The core of a DEA model is comprised of decision making units (DMUs), which in our case are counties. From an input perspective, a DMU is inefficient if one or more DMUs can produce the same amount of output with at least one less unit of input. A DMU is considered inefficient from an output perspective if one or more DMUs can produce more output with the same level of inputs.

V. Data Description

Data was obtained from various New Jersey State and United State federal government databases along with Geolytics, Inc.'s Neighborhood Change Database. The sample contains all 21 New Jersey counties over years 2001-2018. From this list I pulled annual data and categorized the county-years into three groups based on time. After removing those observations with incomplete data or inconsistent reporting, the final datasets for the three periods are 147 county-year observations in the pre-crisis (2001-2007) period, 63 during the crisis (2008-2010)period, and 168 in the post-crisis (2011-2018) period. The overall dataset contains 378 county-year observations represented by 21 different New Jersey counties.

Selecting a DEA output measure for the New Jersey counties presents a challenge. Within the New Jersey municipal system there exist large differences in economic base, location, and population density that complicate the output decision.[7] Given historical macroeconomic studies on economic efficiencies, it is most logical to use *Gross Domestic Product* as the output, as used by Kruger et. Al. (2000) and Forstner and Isaksson (2002) among others. I then divided by each

[7] As Ambrose and Pennington-Cross (2000) outline efficiency studies in other industries often have a homogenous production unit that quantifies firm output such as barrels of beer produced by breweries, freight-tons hauled by railroads, or kilowatt-hours produced by utilities.

counties' population density. This metric helps account for heterogeneity among municipal factors and establishes comparability of the county GDPs.

For inputs, I follow the lead of the aforementioned papers but separate out State and Federal capital funding sources and labor force. My decomposition is slightly more given advancements in data collection. Here, capital funding is divided into three different categories. *NJEDA Funding* is taken directly from New Jersey CAFRs. *Other State Funding* and *Federal Funding* were also obtained from New Jersey municipal CAFRs and then calculated using the same methodology across each municipality. *Labor Force* represents each county's total labor force over the age of 15 years old. This data was obtained from the Bureau of Labor Statistics and calculated by using Geolytics' 2010 county boundary lines. Lastly, *Gross Capital Formation* was obtained and calculated using the Bureau of Labor Statistics database and definition. Just as GDP, all input variables are divided by each counties' population density to account for heterogeneity among municipal sizes. Summary statistics of these variables are shown in Table 2.

VI. Results and Discussion

In this section I present the results of the DEA model. First, I examine the overall economic efficiency. Next, I discuss the sources of inefficiency. Lastly, I conduct a difference-in-difference analysis testing for statistically significant differences between the pre-crisis and post-crisis periods, thus testing for economic efficiency gains post-crisis.

V.1 Overall Economic Efficiency

Table 3 presents a summary of the number of New Jersey counties deemed efficient by the DEA model year over year. The percentages can be interpreted as the portion of counties on the efficient frontier in a given year. Just 14% of the full sample were on the efficient frontier in 2001.

There was then a dramatic rise in the percentage of efficient counties, topping out at 86% in 2006, then followed by a dramatic decline back to 10% by 2010. The end result is 76% efficiency in 2018.

Table 4 provides separate DEA results for both efficient counties (Panel A) and inefficient counties (Panel B), allowing for comparison of the outputs, inputs, and economic efficiency. Output (GDP) is higher for the efficient counties in any given year while economic inputs tend to be mixed, as expected with the DEA model. For example, in 2001 the average GDP output per capita for efficient counties is $5,028, compared to $3,570 for inefficient counties. In addition to much lower starting values the inefficient counties experienced a more dramatic economic decline as their output dropped 28% by 2010, whereas the efficient counties' output fell just 7.4%. Higher output appears to be the strongest distinction between the efficient and inefficient counties. On average, efficient county output is 25% greater than that of the counties off the efficient frontier. Regarding the inputs, advisory fees and property management fees are especially small with respect to total assets.

DEA input efficiency is found in the right-most column of both panels and represents the average operational efficiency for the counties. The average input efficiency is 1.0 for all years in Panel A because the subsample represents only counties on the efficient frontier. Looking at Panel B, the overall trend is a 109% increase in input efficiency from 2001 to 2018 for the counties deemed inefficient. Efficiency increased 102% points following the financial crisis of 2008-2010.

V.2 Factors Affecting Economic Efficiency

Just as important as which counties are efficient from an economic perspective is which factors cause the measurable inefficiency. DEA uses target values, which are a combination of efficient units on the envelopment surface, and calculates inefficiency as the difference between the target and actual measures. This allows one to assess which factors are causing the inefficiencies as well as the necessary adjustments to operate on the efficient frontier. Again, this is an advantage over other methods of measuring economic efficiency. For example, when estimating economic efficiency with a multiple regression model the ability to uncover factors driving inefficiency can be confounded by multicollinearity, however frontier analysis such as DEA avoids this issue.

Table 5 shows the mean inefficiency and relative mean inefficiency for the inefficient counties. The mean inefficiency provides insight into how much a firm's input or output must be increased or decreased to be part of the efficient frontier. Because the DEA model uses each output and input per capita, the interpretation of the figures is the average change in percentage points (ppts) necessary for the inefficient counties to reach the efficient frontier. For example, in Panel A, the 2001 inefficient counties would need to make the following adjustments for each variable to maximize of GDP: Increase NJEDA funding by 38%, reduce the labor force by 2%, increase capital formation by 8%, other state funding by 3%, and federal funding by 1%, while increasing GDP by 4% to meet the target values. To better understand the magnitude of these changes, refer back to the relative size of each input and output in Table 2. In doing this, one will see the percentage point adjustments described above are sizable. For example, observe the 2001 needed increase in total NJEDA funding of 0.38 percentage points. Compared to the mean value of 3.82 in Table 2, this represents about a 10% increase in funding from the NJEDA that was needed in inefficient counties in 2001 to help these counties attain their optimally efficient GDP. Note that even though our DEA model is input driven it still reports an output adjustment for the inefficient counties to reach the efficient frontier. This also highlights the advantage of the DEA method over a regression technique in that it provides measurable changes required to reach the optimal county and State efficiencies.

Panel B of Table 5 shows the mean relative inefficiency measures for counties deemed inefficient. Looking at the inefficient counties provides a clearer view of the drivers of inefficiency. Whereas Panel A revealed necessary adjustments to reach the efficiency frontier, Panel B compares the relative importance of each input with respect to inefficiency. It calculates the measures by dividing the mean inefficiencies in Panel A by the mean value of the given input for the full sample. In all years the *Labor Force*, *Federal Funding* and *Gross Capital Formation* relative mean inefficiencies are predominantly low among the inputs. The other two inputs – NJEDA Funding and Other State Funding – are the main sources of inefficiency, especially during the post-crisis period between 2011 and 2018. These measures experienced the least amount of inefficiency during the liquidity crisis around 2008, 2009 and/or 2010. This is likely due in part to streamlining/ reducing expenses in order to operate within a reduced state budget.

V.3 Significance of DEA Efficiency Difference in a Post-Crisis Period

The second central question of this study centers around whether counties economic efficiency increased following the recent liquidity crisis. While the year-by-year trend already discussed suggests an increase in efficiency, I now run a difference-in-difference test for two reasons. There could be a general time trend of increasing efficiency that is captured in the post-crisis increase. The difference-in-difference helps address these concerns as it measures whether there are statistically significant differences in the DEA efficiency measures between the pre-crisis (2001-2007) and post-crisis (2011-2016) periods.[8] To conduct the analysis, I first take the

[8] I selected these periods in order to use all available data. Since the periods are of slightly different length, I also ran the test with equal periods in which the pre-crisis period was 2001-2007. The levels of significance remained the same with this alternative period length.

differences for each period by subtracting the DEA Efficiency measure for the first year of the period from the DEA Efficiency measure for last year of the period. For example, I subtract 2001's DEA Efficiency measure from 2007's DEA Efficiency measure for the pre-crisis period. Next, we subtract the pre-crisis difference measure from the post-crisis difference measure where the post-crisis measure is the treatment group and the pre-crisis measure is the control group.[9] The measures, standard errors, t-stats, and significance levels are reported for the full sample as well as various subsamples in Table 6. For the full sample I find a statistically significant difference in the DEA efficiency between the pre-crisis and post-crisis periods. Overall, this evidence supports the argument that the rising efficiency in the post-crisis period was not a standard time trend or function of the cross-sectional nature of the data. It further demonstrates the validity of the DEA efficiency measure as a method for conducting economic efficiency analysis among counties. Specifically NJEDA funds have the most significant impact on county and therefore overall State GDP. Other contributors are Other New Jersey State and Federal funds.

This evidence of increasing efficiency following the 2008-2010 crisis begs the question, "why might economic efficiency increase following crisis?" While empirically testing this is beyond the scope of this paper, I can offer a few possible explanations. Perhaps the macroeconomic shock caused inefficient counties to tighten their budgets in the years following the crisis? This could drive the State wide increase in efficiency via a greater impact per dollar of NJEDA, State and Federal funding. In fact, I find that the impact of every dollar invested into the New Jersey economy pre-crisis by the NJEDA generated \$2.78 of GDP. This number increased to \$3.45 post-

[9] I also find statistically significant differences between the pre-crisis and crisis periods as well as the crisis and post-crisis periods using the same difference-in-difference technique.

crisis with real estate invstments. With a needed increase of around 38% from the NJEDA in inefficient counties, this would add $2.78 billion to New Jersey's GDP this year alone.

VII. Conclusion

The present investigation examines New Jersey economic efficiency from 2001 through 2018 via its counties' GDP growth, thus including a complete market cycle of growth, contraction, and recovery. It provides the only quantitative update on how to maximize New Jersey's GDP in an efficient State spending manner during a crisis. Thus quantifying how to best spend funds to bolster the New Jersey economy during a time of crisis such as the COVID-19 outbreak using our most recent financial crisis, the liquidity crisis of 2008-2010.

To do so, I employ the non-parametric technique known as data envelopment analysis (DEA), which maps an efficient frontier for operations on a year-by-year basis. I use datasets from Geolytics Inc., the Bureau of Labor Statistics, New Jersey Consolidated Annual Financial Reports (CAFRs) and the Bureau of Economic Analysis which includes all New Jersey counties operating between 2001 and 2018. The main results provide new evidence that New Jersey counties appear more economically efficient post crisis.

I also consider whether the recent crisis spurred efficiency gains in the State as a whole. The results show an upward trend in economic efficiency for New Jersey between 2001 and 2018, apart from efficiency drops during the crisis. Importantly, the post-crisis period stands out with a more pronounced rise in efficiency. Difference-in-difference estimations show a statistically significant difference in DEA efficiency across the pre-crisis and post-crisis periods for the full sample, mainly in NJEDA, federal, and other NJ State funding sources. Overall, I document an industry low-point for economic efficiency of in 2010 with only 10% of New Jersey counties maximizing GDP. In the post-crisis recovery period efficiency rises back to 76% by 2018. These results hold using various forms of county size measures. The DEA output used is *GDP* while inputs include *NJEDA funding*, *Other New Jersey state funding*, *labor force over 15 years of age*, *Gross Capital Formation*, and *Federal Funding*. Evidence suggests the results might be due to the *NJEDA Funding* and *Other New Jersey State Funding* sources increased efficiencies in identification and investment post-crisis. It is not likely due solely to scale efficiency gains. Therefore, to maximize the State's GDP and in a tight State budget environment, these two sources of funding need to be increased by 25.65% and 49.13%, respectively. These increases would add 22.45% to New Jersey's GDP.

This could drive the State wide increase in efficiency via a greater impact per dollar of NJEDA, State and Federal funding. In fact, I find that the impact of every dollar invested into the New Jersey economy pre-crisis by the NJEDA generated $2.78 of GDP. This number increased to $3.45 post-crisis. With a needed increase of around 38% from the NJEDA in inefficient counties, this would add $2.78 billion to New Jersey's GDP this year alone. Now, more than ever, New Jersey must maximize its incentive spending per dollar or struggle for an extended period through the post-COVID-19 era.

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TABLES

Table 1

Civilian Unempoyment Rate (Seasonally Adjusted)

Panel A. New Jersey			Panel B. United States	
Date	Rate		Date	Rate
Sep-09	9.8%		Sep-09	9.8%
Mar-20	3.7%		Mar-20	3.8%
Jun-20	16.8%		Apr-20	14.8%
Jul-20	13.8%		Jul-20	10.2%

Notes: Percentages represent the monthly Civilian Unemployment Rate for New Jersey (Panel A) and the United States (Panel B) for the given dates.

Table 2						
Sample Summary Statistics						
	Output: GDP	*Input: NJEDA Funding*	*Input: Labor Force*	*Input: Gross Capital Formation*	*Input: Other State Funding*	*input: Federal Funding*
Mean	8.23	3.82	8.28	3.40	2.960	1.380
Median	9.38	4.02	9.71	4.28	2.170	1.420
Min	-14.38	0.00	-24.00	1.33	-8.750	-2.460
Max	27.29	5.38	27.37	7.99	5.090	2.730

Notes: This table presents summary statistics for each DEA output and input variable. The values are presented as a percentage change of each catagory per catipa, as they are scaled in this manner in the DEA model. The entire sample of 378 county-year observations from 2001 through 2018 are including in the statistics.

Table 3

Sample Size by Efficiency Status

Year	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Overall Sample:																
Total Counties	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
Total Efficient Counties	3	7	13	15	16	18	15	5	3	2	3	11	13	15	16	16
Percentage Efficient	14%	33%	62%	71%	76%	86%	71%	24%	14%	10%	14%	52%	62%	71%	76%	76%

Notes: This table presents a time series of the portion of counties identified as efficient by the DEA model results. Counts indicate the number of counties in each category.

Table 4

DEA Results: Output, Inputs, and Efficiency Measurement

Panel A. DEA Efficient REITs

Year	*Output: GDP*	*Input: NJEDA Funding*	*Input: Labor Force*	*Input: Gross Capital Formation*	*Input: Other State Funding*	*input: Federal Funding*	DEA Input Efficiency
2001	5.028	0.285	0.068	0.105	0.130	0.176	1.0000
2002	5.157	0.301	0.089	0.105	0.128	0.186	1.0000
2003	5.058	0.306	0.077	0.114	0.176	0.150	1.0000
2004	5.047	0.322	0.084	0.121	0.141	0.218	1.0000
2005	5.293	0.345	0.102	0.115	0.173	0.169	1.0000
2006	5.857	0.317	0.102	0.133	0.141	0.262	1.0000
2007	6.847	0.384	0.101	0.128	0.183	0.248	1.0000
2008	7.047	0.402	0.065	0.138	0.160	0.236	1.0000
2009	6.133	0.407	0.048	0.132	0.227	0.299	1.0000
2010	6.256	0.453	0.077	0.140	0.235	0.258	1.0000
2011	5.385	0.440	0.079	0.147	0.223	0.276	1.0000
2012	6.485	0.438	0.122	0.184	0.290	0.264	1.0000
2013	6.367	0.528	0.066	0.200	0.245	0.086	1.0000
2014	6.847	0.592	0.069	0.214	0.233	0.026	1.0000
2015	7.250	0.501	0.072	0.247	0.229	0.277	1.0000
2016	7.487	0.527	0.074	0.202	0.043	0.035	1.0000
2017	7.444	0.538	0.089	0.190	0.013	0.074	1.0000
2018	7.483	0.545	0.086	0.194	0.234	0.088	1.0000

Panel B. DEA Inefficient REITs

Year	*Output: GDP*	*Input: NJEDA Funding*	*Input: Labor Force*	*Input: Gross Capital Formation*	*Input: Other State Funding*	*input: Federal Funding*	DEA Input Efficiency
2001	3.570	0.240	0.230	0.191	0.065	0.559	0.2153
2002	3.923	0.515	0.259	0.194	0.515	0.121	0.2498
2003	3.359	0.231	0.187	0.300	0.101	0.375	0.2855
2004	3.513	0.524	0.191	0.243	0.524	0.143	0.3061
2005	3.594	0.270	0.215	0.248	0.108	0.219	0.2422
2006	4.399	0.366	0.195	0.374	0.366	0.302	0.3132
2007	5.313	0.309	0.180	0.272	0.108	0.183	0.3206
2008	5.813	0.210	0.198	0.260	0.210	0.161	0.3216
2009	4.675	0.267	0.248	0.273	0.267	0.254	0.2331
2010	4.557	0.296	0.197	0.398	0.170	0.213	0.2225
2011	3.686	0.365	0.168	0.268	0.148	0.420	0.2629
2012	5.027	0.393	0.273	0.325	0.245	0.199	0.3046
2013	4.833	0.483	0.189	0.481	0.200	0.481	0.4111
2014	5.389	0.377	0.197	0.341	0.377	0.039	0.4001
2015	5.716	0.416	0.170	0.306	0.164	0.202	0.4010
2016	6.253	0.438	0.141	0.335	0.438	0.035	0.3915
2017	5.986	0.463	0.133	0.300	0.052	0.074	0.4345
2018	5.949	0.470	0.135	0.245	0.159	0.088	0.4500

Notes: All values are in 1000s of dollars. Panel A shows average figures for counties operating on the efficient frontier in the DEA results. All percentages are an average of the indicated variable per capita. DEA Input Efficiency is the average input efficiency of the counties in the given year and ranges from 0 to 1, with 1 lying on the efficient frontier. Panel B shows the subset of inefficeinct counties. By design, the average input efficiency in Panel A is on the efficient frontier while Panel B efficiency is well below the full efficiency value of 1.

Table 5

Revealing Sources of Inefficiency for REITs Off the Efficient Frontier

Panel A. Mean Inefficiency Measures

Year	*Output: GDP*	*Input: NJEDA Funding*	*Input: Labor Force*	*Input: Gross Capital Formation*	*Input: Other State Funding*	*Input: Federal Funding*
2001	0.05	0.38	0.02	0.10	1.38	0.98
2002	0.06	1.33	0.49	0.24	1.75	0.95
2003	0.06	1.27	0.21	0.57	1.38	0.76
2004	0.03	1.63	0.35	0.43	1.74	0.79
2005	0.02	1.53	0.70	0.43	1.84	0.82
2006	0.03	1.57	0.38	0.56	2.02	0.78
2007	0.05	1.29	0.37	0.54	1.71	0.89
2008	0.05	1.12	0.32	0.56	1.57	0.95
2009	0.08	0.92	0.42	0.59	1.23	0.78
2010	0.03	0.70	0.34	0.42	1.12	0.45
2011	0.02	1.26	0.25	0.45	1.37	0.80
2012	0.06	1.53	0.51	0.44	1.84	0.76
2013	0.06	1.34	0.32	0.30	1.76	0.95
2014	0.05	1.13	0.58	0.33	1.24	0.01
2015	0.05	1.22	0.11	0.38	2.22	0.98
2016	0.04	1.20	0.22	0.34	1.65	0.99
2017	0.05	1.14	0.26	0.27	1.56	0.78
2018	0.04	0.98	0.20	0.27	1.44	0.55

Panel B. Relative Mean Inefficiency Measures

Year	*Output: GDP*	*Input: NJEDA Funding*	*Input: Labor Force*	*Input: Gross Capital Formation*	*Input: Other State Funding*	*Input: Federal Funding*
2001	0.37	0.73	0.72	0.74	1.42	0.37
2002	0.57	1.32	0.32	0.71	1.22	0.57
2003	0.74	1.44	0.72	0.90	1.00	0.74
2004	0.71	1.80	0.32	0.48	1.26	0.71
2005	0.90	1.75	0.21	0.53	1.11	0.72
2006	0.48	1.15	0.70	0.22	1.03	0.32
2007	0.83	1.64	0.88	0.32	1.24	0.57
2008	0.56	1.34	0.74	0.16	1.32	0.32
2009	0.89	1.14	0.71	0.23	0.95	0.21
2010	0.72	1.05	0.90	0.72	0.62	0.37
2011	0.32	1.48	0.48	0.32	1.02	0.83
2012	0.57	1.42	0.53	0.95	1.15	0.56
2013	0.32	1.51	0.43	0.32	1.30	0.89
2014	0.21	1.48	0.36	0.21	1.34	0.72
2015	0.37	1.44	0.32	0.44	1.20	0.32
2016	0.55	1.73	0.32	0.43	1.34	0.57
2017	0.61	1.23	0.37	0.21	1.00	0.43
2018	0.36	1.15	0.51	0.20	1.42	0.42

Notes: Panel A shows the average percentage points the output (GDP) and inputs need to be adjusted for the inefficient counties to reach the efficient frontier. In any given year if the average inefficient county makes the noted adjustments to all six columns then it will reach the efficient frontier. Panel B has taken the inefficiency measures from Panel A and divided them by the respective output/input for the full sample. It thus offers a measure of the relative importance of each output/input in driving county inefficiency.

Table 6

Difference-in-Difference Across Pre-Crisis and Post-Crisis Periods

	DEA Efficiency Diff-in-Diff		Std. Err.	T-stat
NJEDA Funding	0.2343	***	0.0278	11.38
Labor Force	0.0488		0.0050	1.37
Gross Capital Formation	0.3514		0.1082	0.53
Other State Funding	0.2528	***	0.0127	6.27
Federal Funding	0.0476	**	0.0253	2.54

*Notes: The Pre-Crisis period is 2001-2007 and Post-Crisis period is 2011-2018. The first difference is the difference in average DEA efficiency at the beginning and end of each of the periods. The second difference compares the changes across the two periods. The subsamples are determined by the various management and advisory structures of the counties and are not mutually exclusive. Statistical significance at the 1%, 5% and 10% levels is indicated by *, **, and ***, respectively.*