



Evaluation and Determinants of US Metro Economic Performance

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EXECUTIVE SUMMARY

The Milken Institute has published various reports evaluating urban performance. In addition to its flagship Best-Performing Cities series for both the US and China, the Institute has published two Regional Performance over Time papers to advance our understanding of how urban economies perform across years and the key driving forces behind their success. This paper extends our existing work on regional competitiveness by using a supplementary approach. We hope that this helps our audience learn about the dynamics of urban economies from a new angle.

In evaluating the economic performance of urban economies, some studies construct a single index score from multiple related performance measures and use it for descriptive analysis. Others conduct multivariate analysis by regressing commonly used performance measures, such as employment and wage growth, on a set of explanatory variables. This paper proposes an alternative approach by reducing GDP per capita, labor force participation rate, per capita personal income, and the unemployment rate in 2004, 2006, 2009, and 2014, in which the selected years yield the latest and maximal data while allow for testing the effect of the recent business cycle, into a single principal component as the response variable for regression

¹ Lin, Michael C.Y., Minoli Ratnatunga, and Perry Wong. *Regional Performance Over Time: Thriving and Reviving Amid Economic Challenges*. (Santa Monica: Milken Institute, 2016); Jackson, Jessica, Joe Lee, Michael C.Y. Lin, and Minoli Ratnatunga. *Regional Performance Over Time—Case Study: The Bend-Redmond, Ore.*, *Metropolitan Statistical Area*. (Santa Monica: Milken Institute, 2017).



analysis. The results show that the share of the population with at least a bachelor's degree, the share of manufacturing employment, and establishments born per 10,000 persons, contributed to better economic performance for US metro areas in both 2004 and 2014. Nonetheless, further tests for the recent business cycle reveal that the findings above hold for 2006 but not for 2009, during which only the highly educated share had a major influence on metro performance. This paper also examines how the same set of explanatory variables determines the growth performance from 2004 to 2014. The results show that the non-white population share is the sole variable fueling the growth in all models over the decade. Despite this, the low R-squared values in various growth models indicate that there is a need for further investigation into the growth mechanism.



INTRODUCTION

Over recent decades, a growing number of studies have attempted to measure the economic performance of urban areas, such as Metropolitan Statistical Areas (MSAs) and cities, to identify factors associated with their growth. In assessing economic outcomes, many think tanks have constructed their rankings by collapsing various economic indicators into a single index score. The Milken Institute, for example, has been publishing an annual ranking index of the Best-Performing Cities to trace the economic performance of US MSAs and Chinese cities.² On the other hand, most academic work uses one of the growth rates of population, employment, and/or income to measure the economic performance of urban areas.

In addition to measuring the economic performance of urban areas, a number of studies also examine the contributing factors to urban growth. The index-ranking approach typically intends to offer the general public an intuitive way to compare the relative standing of MSAs and cities. Some ranking reports also provide the reader with descriptive explanations on what contributes to the success of urban economies. Academic studies typically conduct econometric analyses to identify the contributing factors to urban growth.³

The multivariate approach adopted by existing academic studies has advanced our understanding of the economic performance of urban economies and the driving forces behind their growth. Nonetheless, most of them examine a single indicator (e.g., income growth). This approach provides only partial information in representing economic outcomes. Table 1 shows the economic performance of 45 large US MSAs that had a population of at least 1 million based on the 2013-2014 growth rates of four economic indicators. The economic performance of some MSAs is relatively consistent based on the four indicators, whereas the performance of others varies considerably across the four variables. For instance, New Orleans-Metairie, Louisiana, had the highest growth rate on labor force participation (1.07 percent) among all large MSAs over the 2013-2014 period. However, the MSA had the lowest drop in the unemployment rate among its counterparts within the same time. This example reveals the limitations of using a single indicator in evaluating the economic performance of urban areas.

² For the most recent ranking reports for US MSAs and Chinese cities, respectively, see Jackson, Jessica, Joe Lee, Michael C.Y. Lin, and Minoli Ratnatunga. Best-Performing Cities 2018: Where America's Jobs Are Created and Sustained. (Santa Monica: Milken Institute, 2019); Lin, M.C.Y. and Perry Wong. Best-Performing Cities China 2018: The Nation's Most Successful Economies. (Santa Monica: Milken Institute, 2018).

³ See, Glaeser, Edward L., José A. Scheinkman, and Andrei Shleifer. "Economic Growth in a Cross-section of Cities." Journal of Monetary Economics 36, no. 1 (1995). 117-143 and Owyang, Michael T., Jeremy M. Piger, Howard J. Wall, and Christopher H. Wheeler. "The Economic Performance of Cities: A Markov-switching Approach." Journal of Urban Economics 64, no. 3 (2008). 538-550.



Table 1. Large MSA Rankings Based on Economic Growth Indicators (2013-2014)⁴

Metropolitan Statistical Area	GDP Per Capita (Chained. 2009 USD)	Per Capita Personal Income (USD)	Labor Force Participation Rate	Unemployment Rate (Seasonally Adjusted)
San Jose-Sunnyvale-Santa Clara, CA	1 (6.01%)	1 (8.45%)	6 (0.22%)	16 (-1.31%)
Louisville/Jefferson County, KY-IN	2 (5.56%)	28 (4.41%)	42 (-1.23%)	11 (-1.44%)
Miami-Fort Lauderdale-West Palm Beach, FL	3 (5.20%)	3 (7.55%)	8 (0.19%)	32 (-0.89%)
San Antonio-New Braunfels, TX	4 (4.98%)	5 (6.65%)	27 (-0.48%)	22 (-1.13%)
Pittsburgh, PA	5 (3.66%)	33 (4.11%)	30 (-0.57%)	21 (-1.15%)
San Francisco-Oakland-Hayward, CA	6 (3.55%)	4 (7.24%)	16 (-0.22%)	18 (-1.23%)
Los Angeles-Long Beach- Anaheim, CA	7 (3.24%)	11 (5.92%)	14 (-0.17%)	13 (-1.39%)
Dallas-Fort Worth-Arlington, TX	8 (2.57%)	10 (6.07%)	20 (-0.36%)	25 (-1.06%)
Cleveland-Elyria, OH	9 (2.57%)	22 (4.92%)	32 (-0.61%)	38 (-0.78%)
New Orleans-Metairie, LA	10 (2.56%)	14 (5.59%)	1 (1.07%)	45 (-0.26%)

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⁴ 1. If MSAs had a population of at least one million in 2004, they are defined as large MSAs. There are 45 large MSAs; 2. Due to missing data, four MSAs—Denver-Aurora-Lakewood, Colorado; Indianapolis-Carmel-Anderson, Indiana; Virginia Beach-Norfolk-Newport News, Virginia-North Carolina; Washington-Arlington-Alexandria, District of Columbia-Virginia-Maryland-West Virginia—are not included in the analysis.



In addition, few studies have compared urban performance over time. Owyang et al.'s 2008 study is a recent exception that compares the urban performance between high- and low-growth phases.⁵ Moreover, most studies use data gathered before the early 2000s. It would be interesting to see if the determinants of urban growth have changed in more recent decades.

To address the issues above, we propose an alternative strategy and will address three research questions:

- What are the determinants for the performance of urban economies?
- Do the contributing factors of economic performance vary over the recent business cycle?
- How do the past conditions of MSAs affect their economic growth?

Operationally, this study incorporates GDP per capita, per capita personal income, labor force participation rate, and the unemployment rate, to measure the economic performance of US MSAs. The econometric estimation will be conducted in two major steps. First, this study reduces these four variables into a single principal component using a principal component analysis (PCA). Second, the principal component scores in the years of 2004, 2006, 2009, and 2014, as well as the differences between 2004 and 2014, will then be regressed on a set of explanatory variables.⁶

The results show that the shares of college graduates, the share of manufacturing employment, and the number of newborn firms per 10,000 persons are associated with better economic performance in both 2004 and 2014. This study also finds evidence that a higher population density is inversely linked to MSA economic outcomes, whereas the fraction of the non-white population and the number of patents per 100,000 persons are positively related to urban success. The results for 2009 largely resemble those from both 2004 and 2014. Yet only the share of college graduates, which contributes to MSA economic performance, is statistically significant across all three models. This finding suggests that a deeper talent pool is particularly vital for MSAs' economic strength in the face of an economic downturn. In addition, this study finds the non-white population percentage in 2004 was conducive to MSA economic growth from 2004 to 2014. Yet this finding is not robust. Further investigations over the growth mechanisms of urban economies are still needed.

⁵ Owyang, Michael T., Jeremy M. Piger, Howard J. Wall, and Christopher H. Wheeler. "The Economic Performance of Cities: A Markov-switching Approach." *Journal of Urban Economics* 64, no. 3 (2008). 538-550.

⁶ Although data for some variables after 2014 are available, the use of 2014 data allows this work to maximize the number of variables and MSAs used in the study.



LITERATURE REVIEW

The paper builds upon two distinct sets of literature. One branch, beginning with Porter (2003) and extending more recently through Spencer et al. (2010) and Delgado et al. (2014), examines the relationship between regional clusters and their competitiveness or economic performance, primarily in North America and Europe.⁷ Porter (2003) classifies industries into three groups—local industries (e.g., local health services), resource-dependent industries (e.g., mining), and traded industries (e.g., auto assembly), which were used to derive 41 traded clusters in the US. He finds that a stronger regional cluster contributes to employment growth of the industries in the cluster and thus enhances the regional economic performance.⁸ Spencer et al. (2010) examine relationships between the proportion of local employment in clusters and four economic outcome measures across 140 city-regions in Canada. They find that places with a higher percentage of employment in clusters are positively associated with higher average annual income, percentage employment growth, and overall patenting rates, whereas those places are negatively related to the rate of unemployment. Delgado et al. (2014) find that a strong cluster is associated with higher employment and patenting growth of regional industries within a cluster. These empirical studies have developed various ways of defining clusters and used different methods. Nonetheless, they all provide evidence regarding the positive effect of the spatial clustering of industrial activities on regional economic development.

The other branch of literature focuses on the association between urban economies such as MSAs and cities and their economic outcomes. There are two major approaches within this camp. One approach, commonly adopted by think tanks, uses economic indicators, such as job growth, to construct index scores that are then used to rank urban areas. The rankings of urban entities signify their economic performance. The Brookings Institution's Metro Monitor and the Milken Institute's Best-Performing Cities series are two such examples. This approach aims to provide the reader with an instant idea of the economic success of urban areas relative to others. A second branch, typically used by academics, utilizes the growth rates of income/wage, employment/unemployment, or population to measure the economic

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⁷ Porter, Michael. "The Economic Performance of Regions." *Regional Studies* 37, no. 6-7 (2003). 549-578; Spencer, Gregory M., Tara Vinodrai, Meric S. Gertler, and David A. Wolfe. "Do Clusters Make a Difference? Defining and Assessing their Economic Performance." *Regional Studies* 44, no. 6 (2010). 697-715; Delgado, Mercedes, Michael E.Porter, and Scott Stern. "Clusters, Convergence, and Economic Performance." *Research Policy* 43, no. 10 (2014). 1785-1799.

⁸ A strong cluster means its employment in a region is equal to or greater than the region's share of total national employment (i.e., the location quotient or LQ is equal to or greater than one). However, Porter also uses a lower cutoff for cluster strength where LQ is equal to or greater than 0.8.

⁹ Nonetheless, the evidence on patents and unemployment is weaker.



performance of urban areas. Most of these academic works use the average growth rates over a given period.¹⁰

What makes the study of the economic performance of urban economies particularly interesting is not only measuring their performance but also sorting out the driving forces behind their performance. Some ranking reports done by think tanks offer descriptive explanations on urban growth, whereas academic research tends to use econometric methods to estimate empirically the effects of a variety of factors on the economic performance of urban economies. Some empirical papers focus specifically on factors such as human capital (e.g., the percentage of college graduates over the total population) and entrepreneurial activities (e.g., number of establishments). The typical findings from these studies are that higher levels of human capital¹¹ or entrepreneurial activities¹² are conducive to urban growth. Others such as Glaeser et al. (1995) and Owyang et al. (2008) incorporate a more diverse set of variables such as population density, racial diversity (e.g., the share of non-white population), climate conditions (e.g., average July temperature), industrial mix (e.g., the share of manufacturing employment), and geographical dummies (e.g., census regions).¹³

The present study extends the second approach with an alternative method to measure the performance of urban economies. It utilizes the PCA to reduce four economic indicators—GDP per capita, per capita personal income, labor force participation rate, and the unemployment rate—into a single principal component score to measure the overall economic performance of MSAs and explore the determinants of their performance. For a robust check, this study also examines how the recent business cycle affects metro economic performance over time. In addition, this paper further examines how the initial conditions of MSAs affect their economic growth.

¹⁰ Owyang, Michael T., Jeremy M. Piger, Howard J. Wall, and Christopher H. Wheeler. "The Economic Performance of Cities: A Markov-switching Approach." *Journal of Urban Economics* 64, no. 3 (2008). 538-550.

¹¹ Simon, Curtis J. "Human Capital and Metropolitan Employment Growth." *Journal of Urban Economics* 43, no. 2 (1998). 223-243; Simon, Curtis J. and Clark Nardinelli. "Human Capital and the Rise of American Cities, 1900–1990." *Regional Science and Urban Economics* 32, no. 1 (2002). 59-96.

¹² Acs, Zoltan J. and Catherine Armington. "Employment Growth and Entrepreneurial Activity in Cities." *Regional Studies* 38, no. 8 (2004). 911-927; Glaeser, Edward L., Sari Pekkala Kerr, and William R. Kerr. "Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines." *Review of Economics and Statistics* 97, no. 2 (2015). 498-520.

¹³ Glaeser, Edward L., José A. Scheinkman, and Andrei Shleifer. "Economic Growth in a Cross-section of Cities." *Journal of Monetary Economics* 36, no. 1 (1995). 117-143; Owyang, Michael T., Jeremy M. Piger, Howard J. Wall, and Christopher H. Wheeler. "The Economic Performance of Cities: A Markov-switching Approach." *Journal of Urban Economics* 64, no. 3 (2008). 538-550.



DATA AND METHODOLOGY

The data used in this study are from the US Bureau of Economic Analysis, US Bureau of Labor Statistics, US Census Bureau, US Patent and Trademark Office, and Moody's Analytics (Table 2). The latest data this study uses are from 2014 because this year can provide the latest data while maximizing the number of observations from 317 MSAs.

As an alternative to using a single variable as a measure of the economic performance of urban economies, the present study uses the PCA to capture common information by transforming a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. More specifically, the method allows this study to construct the performance measures from four variables with the following steps. First, these variables include GDP per capita, per capita personal income, the labor force participation rate, and the unemployment rate, which are used to obtain four principal component-loading vectors for 2004, 2006, 2009, and 2014. These variables are normalized with a mean of zero and a standard deviation of one. The first principal components for 2004, 2006, 2009, and 2014 are 56.8 percent, 57.1 percent, 60 percent, and 62.4 percent, respectively. The first principal components for these selected years account for the majority of the cumulative total variance among the four variables and thus can explain the largest possible amount of variation in the original variables. Hence, this study uses the scores of the first principal component score vector for each MSA in these years as the measures of economic performance. Next, these principal component scores are regressed on the total population for 2004, 2006, 2009, and 2014 to obtain the residuals for the selected years. These residuals are then standardized and used as the outcome variables ($EconomicPerformance_{mt}$) in MSA m in year t (i.e., 2004, 2006, 2009, or 2014) for the ordinary least squares (OLS) regressions to examine the determinants of economic performance. Using the nonpopulation residuals helps to reduce the influence of population size. The basic functional form of the OLS regression model is as follows:

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\begin{split} &EconomicPerformance_{mt} = \beta_0 + \beta_1 * PopulationDensity_{mt} + \beta_2 * Non - \\ &WhitePopulation_{mt} + \beta_3 * CollegeGraduates_{mt} + \beta_4 * \\ &ManufacturingEmployment_{mt} + \beta_5 * EstablishmentsBorn_{mt} + \beta_6 * Patents_{mt} + \beta_7 * MSASize_{mt} + \beta_8 * CensusDivision + \varepsilon_{mt} \end{split}
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where β_0 is an intercept, followed by a set of variables commonly hypothesized to be determinants of urban growth, and ε_{mt} is a stochastic disturbance.



PopulationDensity is the residential population over MSA land area in square mile; Non — WhitePopulation is the share of non-white population; CollegeGraduates is the share of population 25 years of age or older with at least a bachelor's degree; ManufacturingEmployment is the share of manufacturing employment; EstablishmentsBorn is the number of new firms born per 10,000 persons. Patents is the number of patents granted in the US per 10,000 persons. 14

These variables are all standardized before regressions are conducted. In addition to the aforementioned policy-related variables, this study also categorizes MSAs by population size with the *MSASize* variable. If an MSA in 2004 has a population at least one million, it is defined as a large MSA. If an MSA has a population of at least 500,000 but fewer than one million, it is defined as a medium MSA. If an MSA has a population of fewer than 500,000, it is defined as a small MSA. In addition, this study includes *CensusDivision* dummies to control for geographic variation such as climate and other natural features. Since an MSA's economic performance depends on its past conditions, these explanatory variables are all in one-year lag. This practice may also address the concern of endogeneity bias.

Existing studies typically include population density to measure the agglomeration or congestion effects on local economic development. Studies use the share of the nonwhite population as a proxy for racial/ethnic diversity. The share of college graduates reflects the local talent pool and is expected to contribute to superior economic performance. The share of manufacturing employment typically measures the degree of the industrial mix. The number of new firms can signal the level of entrepreneurial activities. The number of patents reflects the innovation capacity of a locality, with the expectation that this will contribute to economic prosperity. Since previous studies suggest that the economic outcomes and determinants can vary across MSAs with different scales, including an MSA size dummy can account for the variation of MSA sizes. Previous work also includes amenity-related variables such as average January temperature. Although existing studies present evidence on amenity-related growth, policy makers typically have no control over amenities. This study includes Census Division dummies to control for omitted factors (e.g., amenities) that are not being encompassed in the model. Table 2 presents the definitions and sources for variables used in this study (Table A1 and A2 in the Appendix provide the summary statistics for these variables).

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 $^{^{14}}$ Except for $Establishments\ Born\$ and $Patent\$ variables using the 2000 definition, data for other variables are based on the 2010 definition for MSAs by the US Census Bureau.



In addition to the regressions using the level values, this study also conducts "growth regressions" where the outcome variables are computed based on the differences between 2004 and 2014 values, as shown in the following model.

 $\Delta E conomic Performance_m$

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= \beta_0 + \beta_1 * PopulationDensity_{mt} + \beta_2 * Non - WhitePopulation_{mt}
+ \beta_3 * CollegeGraduates_{mt} + \beta_4 * ManufacturingEmployment_{mt}
+ \beta_5 * EstablishmentsBorn_{mt} + \beta_6 * Patents_{mt} + \beta_7 * MSASize_{mt}
+ \beta_8 * Census Division + \varepsilon_m
```

period. 15 β_0 is an intercept, followed by a set of variables used in the level regression

¹⁵ The four variables have mean zero and standard deviation one. The first principal component can explain 56 percent of the variance in the data, and its standard deviation is 1.50, which is the only principal component greater than one.

¹⁶ All explanatory variables are standardized.



Table 2. Definition and Source for Variables

Variable	Definition	Source
GDP Per Capita (USD)	Total real gross domestic product (GDP) per capita (chained 2009 USD) ¹⁷	US Bureau of Economic Analysis
Per Capita Personal Income (USD)	Per capita personal income (USD)	US Bureau of Economic Analysis
Labor Force Participation Rate (%)	Labor force participation rate (%, seasonally adjusted)	US Bureau of Labor Statistics, US Census Bureau, US Bureau of Economic Analysis, and Moody's Analytics
Unemployment Rate (%)	Unemployment rate (%, seasonally adjusted)	US Bureau of Labor Statistics and Moody's Analytics
Population (Person)	Total resident population	US Census Bureau and Moody's Analytics
Population Density (Person/Square Mile)	Population density (person/square mile)	US Census Bureau and Moody's Analytics calculated (using 2010 land area)
Non-White Population (%)	Non-white population (%)	US Census Bureau and Moody's Analytics
College Graduates (%)	Population with a bachelor's degree or higher (age 25 and over) (%, not seasonally adjusted)	US Census Bureau and Moody's Analytics
Manufacturing Employment (%)	Number of manufacturing employment / Number of total employment (%, nonfarm, seasonally adjusted)	US Bureau of Labor Statistics and Moody's Analytics
Establishments Born	Establishments born (number of firms per 10,000 persons)	US Census Bureau and Moody's Analytics
Patent	Number of patents granted in the US (utility patents) (Patenting in technology classes – breakout by origin, US metropolitan areas) (per 10,000 persons)	US Patent and Trademark Office and Moody's Analytics
MSA Size	Large MSA (2004 total residential population ≥ 1,000,000); medium MSA (1,000,000 > 2004 total residential population ≥ 500,000); small MSA (2004 total residential population < 500,000)	
Census Division	Nine divisions defined by the US Census Bureau: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific	

 $^{^{17}}$ The concept of chained-dollars takes into account inflation over time to express amounts in a constant unit of measurement. For example, amounts in every period can be expressed in 2009 dollars by adjusting for the ratio of that year's price level to the 2009 price level.



RESULTS

Table 3 shows the top-performing MSAs classified by their sizes according to the PC scores for both 2004 and 2014. For large MSAs, tech clusters, including San Francisco-Oakland-Hayward, California, San Jose-Sunnyvale-Santa Clara, California, and Seattle-Tacoma-Bellevue, Washington, appear in both years. Two recent emerging tech hubs including Austin-Round Rock, Texas, and Dallas-Fort Worth-Arlington, Texas, entered the top performer list in 2014. Most top-ranked MSAs for the medium and small groups repeat in both years.

Table 3. Top Performers Based on Principal Component Scores

Large MSAs					
Rank	2004	2014			
1	San Francisco-Oakland-Hayward, CA	San Jose-Sunnyvale-Santa Clara, CA			
2	San Jose-Sunnyvale-Santa Clara, CA	San Francisco-Oakland-Hayward, CA			
3	Boston-Cambridge-Newton, MA-NH	Boston-Cambridge-Newton, MA-NH			
4	Seattle-Tacoma-Bellevue, WA	Minneapolis-St. Paul-Bloomington, MN-WI			
5	Minneapolis-St. Paul-Bloomington, MN-WI	Seattle-Tacoma-Bellevue, WA			
6	Hartford-West Hartford-East Hartford, CT	Austin-Round Rock, TX			
7	New York-Newark-Jersey City, NY-NJ-PA	Houston-The Woodlands-Sugar Land, TX			
8	Houston-The Woodlands-Sugar Land, TX	Dallas-Fort Worth-Arlington, TX			
9	San Diego-Carlsbad, CA	Hartford-West Hartford-East Hartford, CT			
10	Chicago-Naperville-Elgin, IL-IN-WI	New York-Newark-Jersey City, NY-NJ-PA			
	Medium M	ISAs			
Rank	Medium M	2014			
Rank 1					
	2004	2014			
1	2004 Bridgeport-Stamford-Norwalk, CT	2014 Bridgeport-Stamford-Norwalk, CT			
1 2	2004 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA	2014 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA			
1 2 3	2004 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI	2014 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI			
1 2 3 4	2004 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA	2014 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA			
1 2 3 4 5	2004 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA Raleigh, NC	2014 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA Salt Lake City, UT			
1 2 3 4 5	2004 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA Raleigh, NC Portland-South Portland, ME	2014 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA Salt Lake City, UT Tulsa, OK			
1 2 3 4 5 6 7	2004 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA Raleigh, NC Portland-South Portland, ME Harrisburg-Carlisle, PA	2014 Bridgeport-Stamford-Norwalk, CT Des Moines-West Des Moines, IA Madison, WI Omaha-Council Bluffs, NE-IA Salt Lake City, UT Tulsa, OK Portland-South Portland, ME			



Table 3. Continued

	Small I	MSAs
Rank	2004	2014
1	Midland, TX	Midland, TX
2	Trenton, NJ	Casper, WY
3	Sioux Falls, SD	Sioux Falls, SD
4	Boulder, CO	Boulder, CO
5	Reno, NV	Odessa, TX
6	Manchester-Nashua, NH	Trenton, NJ
7	Ann Arbor, MI	Anchorage, AK
8	Naples-Immokalee-Marco Island, FL	Fargo, ND-MN
9	Norwich-New London, CT	Burlington-South Burlington, VT
10	Anchorage, AK	Napa, CA

Below is a detailed analysis regarding the three core research questions:

1. What are the determinants for the performance of urban economies?

Table 4 presents the regression results using the 2004 principal component (PC) scores as the outcome variable with all explanatory variables in 2003. Model 1 includes six explanatory variables. The share of college graduates, the share of manufacturing employment, and the number of newborn firms per 10,000 persons are positively associated with a higher PC score (i.e., better economic performance). Model 2 adds an MSA dummy variable to see if MSAs with different population sizes performed differently. The result shows that the MSA size does not have any effects, and the overall results look similar to those derived from Model 1. Model 3 uses dummy variables for the nine census divisions to account for unobserved factors. In addition to the aforementioned three statistically significant variables, population density and the share of the non-white population are also statistically significant. A more diverse demographic pool is conducive to urban economic prosperity whereas a higher population density is inversely associated with economic performance.



Table 4. Ordinary Least Squares Regression (2004)¹⁸

Outcome Variable: Principal Component Score	es for Non-Population S	Standardized Resid	uals (2004)
Explanatory Variables (2003)	Model 1	Model 2	Model 3
Intercept	4.104*10 ⁻¹⁷ (4.118*10 ⁻²)	0.11345 (0.12845)	0.34712** (0.15785)
Population Density (Persons/Square Mile)	-3.136*10 ⁻² (4.504*10 ⁻²)	-0.06042 (0.05083)	-0.12293** (0.05303)
Non-White Population (%)	-1.299*10 ⁻² (4.471*10 ⁻²)	-0.02230 (0.04531)	0.09749** (0.04940)
College Graduates (%)	6.864*10 ^{-1***} (5.929*10 ⁻²)	0.68119*** (0.05937)	0.54765*** (0.05957)
Manufacturing Employment (%)	2.269*10 ^{-1***} (4.814*10 ⁻²)	0.23591*** (0.04850)	0.17987*** (0.05073)
Establishments Born (Number of Firms Per 10,000 Persons)	1.801*10 ^{-1***} (4.802*10 ⁻²)	0.17835*** (0.04815)	0.29808*** (0.05253)
Patent (Per 10,000 Persons)	-5.382*10 ⁻² (5.321*10 ⁻²)	-0.05758 (0.05329)	0.01205 (0.05225)
Medium MSA		-0.00205 (0.16020)	-0.00070 (0.15210)
Small MSA		-0.16082 (0.14665)	-0.14000 (0.13866)
East South Central			-0.46178*** (0.16876)
Middle Atlantic			-0.06767 (0.16437)
Mountain			-0.64206*** (0.19440)
New England			0.44564** (0.21152)
Pacific			-0.55131*** (0.15586)
South Atlantic			-0.47026*** (0.15075)
West North Central			0.42693** (0.18686)
Vest South Central			-0.24872 (0.16502)
Adjusted R ²	0.4625	0.463	0.5311
2-value	0.0000	0.0000	0.0000

 $^{^{18}}$ 1. N=317; 2. Numbers in parentheses are standard errors; 3. East North Central is the reference; 4. ***Significant at the 1% level, **significant at the 5% level, *significant at the 10% level.



Table 5 reports the results using 2014 PC scores as the function of one-year lag (2013) explanatory variables. The results are largely in line with those from Table 4. In Model 1, the share of college graduates, the share of manufacturing employment, and the number of newborn firms per 10,000 persons are all positively related to a higher PC score (i.e., better economic performance). A higher population density is negatively associated with a PC score. Model 2 yields a similar result except that population density no longer plays a role in determining economic outcomes. In Model 3, in addition to the share of college graduates, the share of manufacturing employment, and the number of newborn firms per 10,000 persons, the non-white population percentage, and patents per 10,000 persons are also positively linked to economic performance. Like Model 1, a higher population density is attributed to a lower PC score.

Table 5. Ordinary Least Squares Regression (2014)¹⁹

Outcome Variable: Principal Component Scores for	Non-Population St	andardized Residua	als (2014)
Explanatory Variables (2013)	Model 1	Model 2	Model 3
Intercept	-1.274*10 ⁻¹⁶ (4.449*10 ⁻²)	-0.023978 (0.141520)	0.09272 (0.16158)
Population Density (Persons/Square Mile)	-8.702*10 ⁻² * (4.997*10 ⁻²)	-0.089183 (0.056175)	-0.13032** (0.05473)
Non-White Population (%)	-2.501*10 ⁻³ (4.909*10 ⁻²)	-0.002146 (0.050026)	0.10410** (0.05066)
College Graduates (%)	4.264*10 ⁻¹ *** (6.485*10 ⁻²)	0.421149*** (0.065449)	0.35256*** (0.06331)
Manufacturing Employment (%)	2.426*10 ^{-1***} (5.149*10 ⁻²)	0.245760*** (0.051879)	0.23437*** (0.05040)
Establishments Born (Number of Firms Per 10,000 Persons)	3.256*10 ^{-1***} (5.705*10 ⁻²)	0.330149*** (0.057830)	0.43280*** (0.05771)
Patent (Per 10,000 Persons)	6.250*10 ⁻² (5.624*10 ⁻²)	0.065824 (0.056527)	0.09057* (0.05202)
Medium MSA		0.107220 (0.175765)	0.20800 (0.15677)
Small MSA		0.010526 (0.161948)	0.10984 (0.14365)
East South Central			-0.52597*** (0.17146)

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 $^{^{19}}$ 1. N=317; 2. Numbers in parentheses are standard errors; 3. East North Central is the reference.



Table 5. Continued

Middle Atlantic			-0.08126 (0.16790)
Mountain			-0.72731*** (0.19120)
New England			0.35637 (0.21600)
Pacific			-0.42910*** (0.16186)
South Atlantic			-0.62244*** (0.15630)
West North Central			0.56016*** (0.19110)
West South Central			0.31897* (0.17543)
Adjusted R ²	0.3727	0.3699	0.5144
P-value	0.0000	0.0000	0.0000

The comparison between the two sets of regressions for both years demonstrates several patterns. Consistent for both 2004 and 2014, the share of college graduates, the share of manufacturing employment, and the number of newborn firms per 10,000 persons all register better economic performance of MSAs. Most notably, the parameter estimates for the human capital variable are always highly significant (at 1 percent alpha level) and the largest in terms of the magnitude in most models (except for Model 3 of 2014). The positive effect of the share of manufacturing employment seems to deviate from previous work, which typically finds that larger fractions of employment initially engaged in manufacturing tend to be accompanied by poor economic performance.²⁰ There are at least three possible explanations. First, the share of manufacturing jobs may exert positive effects on economic growth in the mid-run period (e.g., 10 years) as discovered by Simon (1998) and Simon and Nardinelli (2002).²¹ Second, in studying the role of manufacturing jobs on economic development, Scott (2015) argues that the manufacturing sector provides decent wages for less-educated workers. Hence, a larger share of manufacturing jobs may

²⁰ Glaeser, Edward L., José A. Scheinkman, and Andrei Shleifer. "Economic Growth in a Cross-section of Cities." *Journal of Monetary Economics* 36, no. 1 (1995). 117-143; Owyang, Michael T., Jeremy M. Piger, Howard J. Wall, and Christopher H. Wheeler. "The Economic Performance of Cities: A Markov-switching Approach." *Journal of Urban Economics* 64, no. 3 (2008). 538-550.

²¹ Simon, Curtis J. "Human Capital and Metropolitan Employment Growth." *Journal of Urban Economics* 43, no. 2 (1998). 223-243; Simon, Curtis J. and Clark Nardinelli. "Human Capital and the Rise of American Cities, 1900–1990." *Regional Science and Urban Economics* 32, no. 1 (2002). 59-96.



be conducive to local economic growth.²² Third, it is possible that the manufacturing percentage may not truly reflect the industrial mix of a metro area.²³ For the explanatory power of these models, the adjusted R-squares are higher for 2004 regressions than those for 2014. All the variance inflation factors (VIFs) of regressions for both years are well below four and, as such, there are no obvious concerns for multicollinearity.

2. Do the contributing factors of economic performance vary over the recent business cycle?

This section tests if business cycles play any role in changing the determinants of urban performance. The present study conducts two separate sets of regression analyses where the year 2006 represents the peak of the most recent business cycle, and the year 2009 signifies the trough of the cycle. Table 6 lists the modeling results of using 2006 PC scores as a function of the same set of explanatory variables in 2005. Similar to the findings of 2004 and 2014, the college graduates percentage, the share of manufacturing jobs, and the newborn firms per 10,000 persons are all statistically significant at 1 percent alpha level and are positively associated with the economic performance of MSAs in all three models. Like the results from Model 3 of 2004 regressions, a higher population density is inversely linked to urban performance while a more diverse demographic profile is positively related to economic prosperity.

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²² Scott, Robert E. "The Manufacturing Footprint and the Importance of U.S. Manufacturing Jobs," Briefing Paper #388, (Washington, DC.: Economic Policy Institute, 2015).

²³ One alternative is to use other measures such as the Hirschman–Herfindahl index, which measures occupational concentration by industry.



Table 6. Ordinary Least Squares Regression (2006)²⁴

Explanatory Variables (2005)	Model 1	Model 2	Model 3
Intercept	5.124*10 ⁻¹⁷ (4.149*10 ⁻²)	0.102522 (0.129687)	0.234354 (0.160814)
Population Density (Persons/Square Mile)	-4.963*10 ⁻² (4.553*10 ⁻²)	-0.076882 (0.051403)	-0.109943** (0.054006)
Non-White Population (%)	3.278*10 ⁻² (4.523*10 ⁻²)	0.023921 (0.045892)	0.130524** (0.050983)
College Graduates (%)	6.331*10 ^{-1***} (5.814*10 ⁻²)	0.627438*** (0.058260)	0.521961*** (0.059300)
1anufacturing Employment (%)	2.024*10 ^{-1***} (4.879*10 ⁻²)	0.210531*** (0.049113)	0.183760*** (0.051772)
stablishments Born (Number of Firms Per 10,000 Persons)	2.661*10 ^{-1***} (4.852*10 ⁻²)	0.264118*** (0.048682)	0.373689*** (0.054573)
atent (Per 10,000 Persons)	-5.036*10 ⁻² (5.277*10 ⁻²)	-0.052241 (0.052815)	0.006414 (0.052430)
1edium MSA		0.009288 (0.161455)	0.039074 (0.155113)
mall MSA		-0.147779 (0.148159)	-0.093509 (0.141712)
ast South Central			-0.380419** (0.171703)
1iddle Atlantic			-0.094422 (0.167314
1ountain			-0.479322** (0.196722)
lew England			0.431188** (0.215485)
acific			-0.452759*** (0.160308)
outh Atlantic			-0.428346*** (0.157834)
est North Central			0.467274** (0.189600)
est South Central			0.010910 (0.167587)
djusted R ²	0.4543	0.4544	0.5132
Adjusted R ² P-value	0.4543 0.0000	0.4544 0.0000	0.5132

 $^{^{24}}$ 1. N=317; 2. Numbers in parentheses are standard errors; 3. East North Central is the reference.



There are some notable changes when the study uses the 2009 PC scores to regress on lagged explanatory variables in 2008 as shown in Table 7. In the first and second models, the only significant variable is the share of college graduates that help improve the economic performance of MSAs. In Model 3, this variable, together with the share of non-white population and the newborn firms per 10,000 persons, all contribute to superior urban performance. As was previously discovered, a higher population density does not promote urban performance.



Table 7. Ordinary Least Squares Regression (2009)²⁵

Outcome Variable: Principal Component Scores f	or Non-Population Sta	ndardized Residua	ıls (2009)
Explanatory Variables (2008)	Model 1	Model 2	Model 3
Intercept	-4.364*10 ⁻¹⁷ (4.464*10 ⁻²)	-0.005965 (0.140872)	-0.03913 (0.16486)
Population Density (Persons/Square Mile)	-7.497*10 ⁻² (4.938*10 ⁻²)	-0.075819 (0.055927)	-0.11375** (0.05553)
Non-White Population (%)	-1.727*10 ⁻³ (4.859*10 ⁻²)	-0.001899 (0.049505)	0.13787*** (0.05120)
College Graduates (%)	6.056*10 ^{-1***} (6.331*10 ⁻²)	0.604202*** (0.063774)	0.49661*** (0.06306)
Manufacturing Employment (%)	5.761*10 ⁻² (5.155*10 ⁻²)	0.058612 (0.052025)	0.07790 (0.05165)
Establishments Born (Number of Firms Per 10,000 Persons)	8.257*10 ⁻² (5.451*10 ⁻²)	0.083643 (0.055141)	0.20470*** (0.05841)
Patent (Per 10,000 Persons)	6.348*10 ⁻³ (5.562*10 ⁻²)	0.006936 (0.055879)	0.03521 (0.05282)
Medium MSA		0.033583 (0.175325)	0.09851 (0.16031)
Small MSA		0.001099 (0.161025)	0.09085 (0.14641)
East South Central			-0.44068** (0.17580)
Middle Atlantic			0.18399 (0.17122)
Mountain			-0.37751* (0.20574)
New England			0.75636*** (0.22142)
Pacific			-0.20384 (0.16623)
South Atlantic			-0.45468*** (0.15818)
West North Central			0.79358*** (0.19458)
West South Central			0.33665* (0.17463)
Adjusted R ²	0.3683	0.3644	0.4868
P-value	0.0000	0.0000	0.0000

The results for 2006 regressions are similar to those from 2004 and 2014. The college graduates percentage, the share of manufacturing employment, and the newborn firms per 10,000 persons are all statistically significant at 1 percent alpha level and positively associated with the economic performance of urban areas. A

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 $^{^{25}}$ 1. N=317; 2. Numbers in parentheses are standard errors; 3. East North Central is the reference.



higher population density is inversely related to urban performance, whereas demographic diversity is associated with economic prosperity. The 2009 regressions reveal some distinct results. The share of college graduates become the only variable with statistical significance in the first two models. Despite similarities to the 2006 results of Model 3, the effects of the share of manufacturing employment disappear after controlling for both MSA size and census division dummies. Among all significant variables across various sets of models, the human capital variable has the largest effect on better economic outcomes. The findings here suggest that the talent pool plays an even more critical role in determining the economic performance of MSAs in the face of the economic trough. Overall, the adjusted R-squares are higher for 2006 than those for 2009. All VIFs of regressions for both years are well below four, and thus no multicollinearity exists.

3. How do the past conditions of MSAs affect their economic growth?

Table 8 shows the OLS regression results where the outcome variable is equal to the PC scores of reducing the growth rates of four economic performance measurements between 2004 and 2014 into one dimension. The results from the three growth models are fairly consistent. The level of the non-white population in 2004 is positively related to MSA growth between 2004 and 2014. Except for the result in Model 3, the 2004 manufacturing employment level and newborn firms per 100,000 persons are positively associated with MSA growth. Compared with the East North Central Census Division (Indiana, Illinois, Michigan, Ohio, and Wisconsin), the West North Central Census Division (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota) and the West South Central Census Division (Arkansas, Louisiana, Oklahoma, and Texas) performed worse. All VIFs of regression models are well below four and thus show no salient signal of multicollinearity. However, except for Model 3, the R-squares of the growth models are fairly low—the first two models can only explain approximately 3 percent of the variation of the outcome variable. These findings suggest the need for further investigating the association between the initial level of MSA conditions and the growth of MSAs using PCA.



Table 8. Ordinary Least Squares Regression (2004-2014)²⁶

Outcome Variable: Principal Component Score (2004-2014 Change)							
Explanatory Variables (2004)	Model 1	Model 2	Model 3				
Intercept	-2.844*10 ⁻¹⁷ (8.281*10 ⁻²)	-0.1358276 (0.2589528)	0.40025 (0.29592)				
Population Density (Persons/Square Mile)	-7.321*10 ⁻³ (9.068*10 ⁻²)	0.0007578 (0.1024151)	-0.12492 (0.09956)				
Non-White Population (%)	2.297*10 ^{-1**} (9.030*10 ⁻²)	0.2321372** (0.0916596)	0.22192** (0.09393)				
College Graduates (%)	-9.670*10 ⁻² (1.179*10 ⁻¹)	-0.1020915 (0.1180905)	-0.17990 (0.11034)				
Manufacturing Employment (%)	2.401*10 ⁻¹ ** (9.760*10 ⁻²)	0.2455043** (0.0983148)	0.05290 (0.09634)				
Establishments Born (Number of Firms Per 10,000 Persons)	2.395*10 ^{-1**} (9.659*10 ⁻²)	0.2469421** (0.0970048)	0.10607 (0.10015)				
Patent (Per 10,000 Persons)	-1.042*10 ⁻¹ (1.061*10 ⁻¹)	-0.1022236 (0.1063242)	-0.08787 (0.09797)				
Medium MSA		0.3890812 (0.3225352)	0.09719 (0.28656)				
Small MSA		0.1075891 (0.2957715)	-0.16843 (0.26145)				
East South Central			0.14268 (0.31664)				
Middle Atlantic			-0.18896 (0.30967)				
Mountain			0.06364 (0.36325)				
New England			0.19855 (0.39806)				
Pacific			-0.24167 (0.29017)				
South Atlantic			0.27112 (0.29002)				
West North Central			-0.81677** (0.35025)				
West South Central			-2.29269*** (0.30802)				
Adjusted R ²	0.03019	0.02985	0.2601				
P-value	0.01641	0.02621	9.246*10 ⁻¹⁶				

 $^{^{26}}$ 1. N=317; 2. Numbers in parentheses are standard errors; 3. East North Central is the reference.



CONCLUSION

This paper proposes an alternative approach to measure urban economic performance and examines the determinants driving urban success. It finds that the share of college graduates, the fraction of manufacturing employment, and the number of newborn firms per 10,000 persons exerted positive effects on metro performance in 2004, 2006, and 2014. For 2009, however, only the share of college graduates mattered in all model specifications. These findings suggest that a deeper talent pool is conducive to metro economic health, particularly in the face of an economic downturn.

When the analysis controls for both MSA size and census division (Model 3), population density is negatively associated with MSA economic performance for the four selected years.²⁷ A number of previous studies have found that denser places should have higher productivity due to agglomeration economies. However, as Gordon and Ikeda (2011) and Lin (2013) have argued, since there is a tremendous variety of traditional density measures across metropolitan areas, using metro density may mask some association between metro characteristics.²⁸ Hence, the insignificance of the density variable may not come as a surprise. The share of the non-white population contributes to better urban performance in Model 3 for all years. Although there is also some evidence that there is a positive relationship between the number of patents and metro economic outcomes, this result only occurs in Model 3 of 2014 and hence may need further investigation.

The present study also regresses the PC score change between 2004 and 2014 on the same set of the explanatory variable used in previous analyses. The share of the non-white population becomes the only variable that matters across three models. The manufacturing employment percentage and the number of newborn firms per 10,000 persons register superior economic performance in the first two models but not in Model 3. The share of college graduates has no effects on metro growth, which stands somewhat at odds with most existing research.²⁹ The low R-squares for the growth regressions suggest that developing better models under the PCA framework remains an important avenue of future research.

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²⁷ The only exception happens in Model 1 of 2014, where the density variable is also inversely associated with urban economic performance.

²⁸ Gordon, Peter and Sanford Ikeda. "Does Density Matter?." In *Handbook of Creative Cities*, edited by David Emanuel Andersson, Åke E. Andersson, and Charlotta Mellander, 435-455. Northampton: Edward Elgar, 2011; Lin, C. Y. "Talent Migration: Does Urban Density Matter?." PhD diss., (University of Southern California, 2013).

²⁹ See, Simon, Curtis J. and Clark Nardinelli. "Human Capital and the Rise of American Cities, 1900–1990." *Regional Science and Urban Economics* 32, no. 1 (2002). 59-96, for instance.



APPENDIX

Table A1. Descriptive Statistics (2004 Regressions)

Variable	Mean	Median	SD	Minimum	Q1	Q3	Maximum
GDP Per Capita (USD) (2004)	41,656	40,135	10,776	19,624	33,791	47,830	101,676
Per Capita Personal Income (USD) (2004)	31,203	30,064	5,819	16,958	27,552	33,770	68,791
Labor Force Participation Rate (%) (2004)	65.72	65.44	5.06	44.76	62.64	68.93	82.32
Unemployment Rate (%) (2004)	5.60	5.34	1.63	2.95	4.57	6.19	17.00
Population (Person) (2003)	715,165	266,584	1,618,884	55,234	147,386	573,376	19,248,311
Population Density (Person/Square Mile) (2003)	280	188	324	7	110	326	2,619
Non-White Population (%) (2003)	15.27	12.05	10.87	1.98	7.24	20.76	77.41
College Graduates (%) (2003)	24.32	23.60	7.43	9.81	19.13	28.77	56.26
Manufacturing Employment (%) (2003)	12.32	11.18	6.82	1.29	7.48	15.69	48.23
Establishments Born (Number of Firms per 10,000 Persons) (2003)	25.01	23.53	7.04	5.70	19.92	28.45	58.66
Patent (Number of Patents Per 10,000 Persons) (2003)	2.74	1.44	4.15	0.00	0.75	3.08	39.78

N=317



Table A2. Descriptive Statistics (2014 Regressions)

Variable	Mean	Median	SD	Minimum	Q1	Q3	Maximum
GDP Per Capita (USD) (2014)	42,424	40,334	14,248	18,065	33,401	48,282	178,711
Per Capita Personal Income (USD) (2014)	42,643	40,969	9,522	24,365	36,797	45,877	117,163
Labor Force Participation Rate (%) (2014)	62.27	62.16	4.95	45.83	59.05	65.48	77.57
Unemployment Rate (%) (2014)	6.28	6.09	2.13	2.69	5.10	6.99	24.05
Population (Person) (2013)	786,760	280,156	1,728,194	53,791	156,025	638,177	20,023,110
Population Density (Person/Square Mile) (2013)	302	206	340	7	117	351	2,709
Non-White Population (%) (2013)	17.52	14.89	11.11	2.25	9.31	23.06	77.70
College Graduates (%) (2013)	26.76	26.22	7.99	11.28	20.84	32.03	58.53
Manufacturing Employment (%) (2013)	10.09	8.79	5.99	0.77	6.00	12.86	46.15
Establishments Born (Number of Firms per 10,000 Persons) (2013)	17.69	16.59	5.30	3.36	13.81	20.77	38.24
Patent (Number of Patents Per 10,000 Persons) (2013)	3.39	1.83	5.59	0.00	0.84	3.80	66.89

N=317



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Michael C.Y. Lin is a senior research associate at the Milken Institute's Center for Regional Economics. His current research focuses on evaluating urban and regional economic performance and exploring the determinants of their growth and decline. He was also involved in writing several policy reports on green buildings, sustainable community development, and informal housing. Dr. Lin published articles in *Annals of Regional Science*, and two book chapters in community planning and shrinking cities. He has also been participating in peer reviews for various academic journal articles. In addition to being an urban and regional economist, Dr. Lin is also a data scientist utilizing both econometric and machine learning methods in his research, which grants him to teach students in using Python, R, SAS, and SPSS for data analysis at the University of Southern California (USC).

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