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GROWTH, STABILITY, AND RESILIENCE OF U.S. METROPOLITAN REGIONS, 1990-2017

by

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ABSTRACT OF THE DISSERTATION

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Various national and regional socioeconomic shocks such as recessions can affect the stability of regional economies. Still, regions react in diverse ways to the same forces; some recover slowly despite being less affected while others recover rapidly despite being heavily impacted. To examine the dynamics of regional economies, this study focuses on the extent to which a region can avoid faltering in a crisis (stability) and how quickly it can respond positively to the crisis (resilience), while sustaining a long-run pattern of expansion (growth). This study presents two new measures of recessionary periods of 382 U.S. metropolitan areas for stability and resilience, in addition to the use of the overall growth rate, using monthly data from January 1990 through March 2017.

This study categorizes metropolitan areas into eight categories by using nationwide or median figures. Results demonstrate that a good deal of variation exists among metropolitan areas in terms of growth, stability, and resilience and that only a few are relatively stable and resilient while growing fast. Four of the eight categories are heavily loaded, with each containing slightly less than 20% of all metropolitan areas. Curiously, two are the categories of metropolitan areas that grew fast and were stable; the others are the polar opposite set, which grew slowly and were unstable. This suggests that stable metropolitan areas tend to grow faster but the level of resilience varies greatly among them.

This study then examines the geography of the outcomes of the classification scheme. As established elsewhere, from 1990 to 2017 metropolitan areas of the Northeast grew slowly, and those of the West and South were more apt to grow more rapidly. These general growth trends are undoubtedly at least partly connected to general geographic changes in trade patterns which moved away from Europe and toward Mexico and the Pacific Rim. Less well known over the study period is that metropolitan areas of the Northeast were also more unstable than most of their equivalents elsewhere in the U.S., and those in the U.S. West tended to be more resilient to their own vagaries.

To identify explanatory variables that affect growth, stability, and resilience, this study performs seemingly unrelated regression, three-stage least squares, and categorical analyses. A few variables have shown statistical significance on the metropolitan employment dynamics, regardless of national recession periods, Census Regions, or economy scales. The wide applicability of these variables may thus be suitable for consideration as a federal policy. Other variables showing statistical significance for a particular time, region, or economy scale may help set goals for specific metropolitan areas.

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DEDICATION

For Mom and Dad

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CHAPTER 1. INTRODUCTION

1. Aims and Scope

The Great Recession officially began in the United States in December 2007 and ended in June 2009, according to the National Bureau of Economic Research. Over this 17-month recession, the stability of many regional economies was substantially and adversely impacted, resulting in significant employment loss. Economic data illustrate how individual metropolitan areas performed and maintained economic activity throughout the downturn and recovery. The Phoenix-Mesa-Scottsdale Metropolitan Statistical Area (MSA) in Arizona experienced consecutive monthly employment losses during this period, except for three months, as did the Orlando, Florida, MSA. The Yuma, Arizona, MSA lost 35 percent of its employment by the end of the recession, the most substantial loss of any MSA.¹

Although the economic data indicate widespread and continued employment loss during the Great Recession, they also reveal that the severity of regional impacts varied as economies reacted in different ways. The San Antonio-New Braunfels, Texas, MSA experienced a decline in employment for only four nonconsecutive months and each monthly loss was 2.7 percent or less. The effects of the recession in the Great Falls, Montana, MSA were similar to those in San Antonio with respect to the length and depth of its economic hardship. The employment in a small MSA in New Jersey, Ocean City, even increased by 35 percent during the recession.

¹ Metro areas' performances discussed here in the introduction are based on the seasonally unadjusted Quarterly Census of Employment and Wages. The data are later seasonally adjusted by the author for the analysis.

Clearly, subregions can react in a variety of ways to negative forces that are detectable nationwide. Of course, there are many localized socioeconomic shocks that can affect the stability of regional economies as well. While some regions are less affected and recover faster, others suffer or stagnate through long recovery periods. Some may not even recover within a fairly long-run timeframe. Policy makers are eager to discover what causes impacts in some regions to be minimally negative and what enables regions to recover fast from economic shocks. Current discussions on quick recovery prompted by the recent recession have focused on the term and concept of "resilience," which generally refers to the ability of an economy to return to its pre-shock status. The Office of Sustainable Housing and Communities in the Department of Housing and Urban Development was renamed the Office of Economic Resilience in 2014, which concentrates on bolstering preparedness for economic shocks. Not-for-profit organizations including the Community and Regional Resilience Institute also support this initiative. Indeed, several conferences have been held within the past few years on the topic. To further the ongoing research addressing the question of what makes regions resilient and strong against outside forces, comprehensive analyses of regional economic growth are sorely needed.

A review of economic literature reveals several views of the dynamics of a "good" regional economy. While some researchers emphasize the importance of a high growth rate, others suggest *steady* growth is even better. Some authors note that regional economies that have reached a critical point in development are "good," while others suggest that comparisons are needed to identify the quality of growth. Despite these discrepancies in theory, it seems clear that a region growing fast and steadily while at an advanced stage of development are clearly at the peak of regional economic health. But it

is difficult to compare regions that display marginal variations in the many possible criteria that are available to measure the quality of a regional economy. Therefore, I limit comparisons to three core aspects of regional economies: growth, stability, and resilience; further, I suggest it is preferable that a regional economy grows rapidly, is stable, and is resilient.

The experience of faltering regional economies caused by the 2007-2009 recession and the recent rising interest in sustainable development has renewed attention to ways in which regional economies might enhance their sustainability. Therefore, this study focuses on the extent to which a region can avoid faltering in a crisis (stability) and how quickly it can respond positively to the crisis (resilience), while sustaining a long-run pattern of expansion (growth). The latter has always been a core concern of regional economic development. A three-dimensional projection of these three aspects of regional economy is shown in Figure 1. This study aims to propose a straightforward and rational measure for each concept, and categorize regional economies into eight categories by using nationwide or median figures. The upper right, back cube of the eight cubes is the most desirable category for any regional economy to belong and the lower left, front cube is the least desirable.

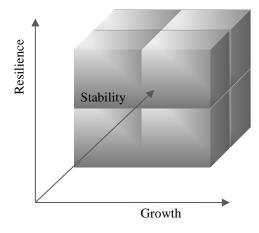


Figure 1. Categories of Regional Economy

Note that the above figure does not assert that the three angles must be considered with an identical degree of importance. Growth only shows the long-run trend without details and thus additional aspects are necessary for a comprehensive understanding of the dynamics. Once stability and resilience are ensured in addition to growth, one may conclude that a region has a healthy economy both in the long- and run-run and both broadly and in detail. In that, three aspects must be considered all together to properly show the full picture. At the same time, each of these measures has its own effects on a region and hence its own policy implications. A metropolitan area is likely to prioritize one of the three measures depending on the time and situation where it belongs. There may be a pressing need for expansion within a newly formed metropolitan area, stabilization may be the urgent interest to those who are under a shock, and those who are hard hit are likely to prioritize a quick recovery.

The reasons why the issue of regional economic resilience and stability needs to be examined along with long-term growth are twofold. First, volatility, the opposite of stability, has seemed to increase across regional economies within the past few decades; and volatile regional economies generate several practical predicaments. If the problem of volatile regional economies is ignored, each member of society, from individuals to firms, as well as local governments and the federal government, will be affected. Individuals will experience continuing unemployment due to unhealthy regional economies. Changes in the level of production and the number of employees can decrease firms' productivity if they continue to invest in such regions. Local governments, which aim to maximize benefits from their constrained financial resources by allocating those resources to certain purposes, may spend their funds inefficiently to bolster their fluctuating or declining economies. Worse still, those who lose their jobs in one region often leave for new jobs elsewhere, resulting in downward spiral in tax revenues and an ever-more fragile economy. In addition, social disorder that may be induced by widespread unemployment and heightened income inequality, can burden governments.

In this study, I examine regional economic growth patterns in the United States for the 1990 to 2017 period, through quantitative analyses. The overarching research question is: how can an MSA economy become more stable and more resilient while maintaining its long-term growth? This question is addressed through answering a set of sub-questions: 1) How are growth, stability, and resilience defined?; 2) How have MSAs performed in terms of growth, stability, and resilience since 1990?; 3) What internal and external factors to MSA economies, including those that were theorized to be important remain unrepresented in existing empirical evaluations, induce the most variation in their growth, stability, and resilience?; 4) What can government officials of MSA economies do to enable faster growth, greater stability, and increased resiliency simultaneously? Although other measures could be used to evaluate the three dimensions of regional change economic that I pursue here, this study focuses on employment as the fundamental aim of a political economic system. Jobs relate to votes, and alternatively, a lack of jobs is highly related to political unrest. Other measurements, such as GDP, aggregate personal income, and a level of happiness among residents of an MSA, could have been included instead, and should in fact be examined in future research.

I use MSAs as the geographic focus because MSAs reflect the smallest functional economic boundaries for regional employment. Individuals are likely to work in the same MSA in which they live, but a large portion of them may work outside the same city or county in which they live. MSAs been designed and accepted as fundamental labor market areas while most other spatial configurations of municipalities are not.

This study builds on the premise that an MSA's growth, stability, and resilience depend on both internal and external factors. Endogenous factors within an MSA, such as demographic factors, economic features, policies, or practices, can help the MSA cope with a volatile economy, while an MSA's stability and resilience remain dependent on some exogenous factors, such as state policies and global corporations. This study therefore takes both internal and external factors into account.

This study is expected to contribute to the literature and the real world in four ways. First, the implementation of two new measure for economic dynamics, in addition to the traditional growth measure, this study breaks the growth-is-the-best ideology, while not entirely dropping the importance of the long-run pattern of expansion. Second, the budding concept of resilience is often criticized for its ambiguity and will be more useful only as it becomes firmly grounded in consistent methods. The two new measures for stability and resilience, which will be described in detail in Chapter 2, are developed to avoid any author-defined arbitrary boundaries on time or the degree of fluctuations. The ability to capture local fluctuations through these measures removes the necessity of including an author-defined time limit in national-recession-based studies. Furthermore, the increased generalizability of these measures in turn generates an increased applicability to other regions, nations, time periods, allowing for easier comparison across regions, nations, and time periods. Due to the simplicity of generalizability of these measures, formulae to be proposed in Chapter 2 may even be applied without further modification to various units of analysis including but not limited to GDP, wages, and well-being of individuals. Third, the use of simultaneous regressions, that has not appeared in related literature, allows for a more complete examination of economic dynamics. Lastly, the list of independent variables to be included in models is limited to those that have been discussed in theories and those that have only been suggested for future studies in empirical research, in addition to the ones that appear in empirical studies. This comprehensive list attempts to discover which of the variables are more impactful in the real world.

The following sections begin with a discussion of how growth theories have developed and how they have addressed regional economic stability and resilience in them. As resilience is a relatively new and less clear concept, unlike growth and stability, this section outlines how resilience is defined in various fields, at least conceptually, and how this terminology is used in regional economics. A discussion follows on how empirical research has examined regional economic stability and resilience. Here, the concept of resilience is realized in quantitative empirical studies. This chapter concludes with the ways in which this study may contribute to existing literature.

2. Growth Theories

Growth theories linked later to economic fluctuation research consist of the neoclassical growth model, the AK model, the product-variety model that includes the Schumpeterian model, and the portfolio model. The neoclassical model, first constructed by Solow (1956) and Swan (1956), emphasizes the role of capital accumulation in growth. The central idea of this model is expressed by the following two equations:

$$Y = AK^{\alpha}L^{1-\alpha}$$
$$\dot{K} = sY - \delta K$$

where Y is current output, A is a productivity parameter (i.e., the rate of technological progress), K is the current supply of capital, L is the current supply of labor, α is less than 1 to reflect decreasing returns to capital, K is capital accumulation, sY is aggregate savings (investment), and δ K denotes aggregate depreciation of capital. These two equations imply that an increase in **savings** increases capital, an increase in capital increases output, and the increased output brings economic growth. The equations are also based on the assumption of diminishing returns to capital, resulting in a long-run growth rate equal to the productivity parameter A, which is determined exogenously by noneconomic factors. In other words, policies that induce people to save more may accomplish economic growth to some extent, but no policy will foster long-run economic growth because the productivity parameter is determined exogenously and the internal economic system, including the government policies, will not change the productivity parameter.

The AK model, developed by Harrod (1939) and Domar (1946), is a neoclassical model without the assumption of diminishing returns to capital. Firms maximize profits when capital and labor expenses equal their marginal products with no investment for technological development. This process increases the marginal product of capital, which offsets the diminishing returns to capital under a certain level of technology. Therefore, this model generates a production function of Y = AK, where Y is output, A is a constant, and K is capital. The constant A in this function is equal to marginal product of capital. This model is called the AK model because of this functional form. By using this basic equation, Y = AK, and an additional equation used in the neoclassical model, $\dot{K} = sY - \delta K$, the (short- and) long-run growth rate can be derived as follows:

$$g = \frac{\dot{K}}{K} = sA - \delta$$

This model shows that an economy's long-run growth rate depends on the rate of saving, the rate of capital depreciation, and a constant A that accounts for technological development. Compared to the neoclassical model, this model projects an economy's long-run growth rate that depends on economic conditions internal to the economic system including **technological development**. Although the neoclassical model shows that the rate of technological progress is determined exogenously, technological progress can and needs to be seen as an endogenous factor. Various activities within the economic system, such as industrial development, competition of firms, and cooperation of entrepreneurs, are attributable to the technological progress. Arrow (1962) viewed technological progress as a natural consequence that was achieved by "learning by doing."

The product-variety model centers on **innovation** and is classified into two sub models: Romer's model and the Schumpeterian model. In Romer's (1990) model, innovation creates new, but not necessarily improved, products and, therefore, increases productivity. Romer's model originates from Dixit and Stiglitz's (1977) production function,

$$Y_t = \sum_0^{N_t} K_{it}^{\alpha} di,$$

where Y_t is the output at time t, N_t is a number of intermediate products at time t, and K_{it} is a unit of capital used to produce product i at time t. This production function can also be written as $Y_t = N_t^{1-\alpha} K_t^{\alpha}$. Despite the assumption of diminishing returns to capital, an increase in the variety of products enables capital investment to be diversified across industries, resulting in the production potential. According to this model, exit and turnover that may occur during the process of innovation reduce the number of intermediate products, reducing GDP, therefore causing a negative impact on growth.

Alternatively, the Schumpeterian model states that a random series of qualityimproving innovations drive growth and creative destruction associated with the process of quality-improving innovation is critical in growth (Schumpeter, 1942). The production function used in the Schumpeterian model is

$$Y_{it} = A_{it}^{1-\alpha} K_{it}^{\alpha}, \qquad 0 < \alpha < 1$$

where Y_{it} is the industry-specific output at time t, A_{it} is a productivity parameter attached to the most recent technology used in industry i at time t, and K_{it} is the flow of a unique intermediate product used in industry i at time t. Each intermediate product is produced by the most recent innovator, who increases A_{it} ; A_{it} increases again when the next innovator replaces the current innovator. Therefore, fast growth means a high rate of turnover. Aggregate output is

$$Y_t = A_t^{1-\alpha} K_t^{\alpha}$$

where A_t is the sum of A_{it} s and K_t is the sum of K_{it} s. Though the aggregate output function looks similar to that of the neoclassical model, its A_t is endogenously determined whereas the neoclassical model's A_t is an exogenous factor.

Lastly, the portfolio model views economies as a **portfolio of industries**, each of which grows at a rate that is to some degree correlated with the growth rates of other industries (Conroy, 1975). This framework has been supported continuously by other researchers such as Brown and Pheasant (1985), Malizia and Ke (1993), Siegel, Johnson and Alwang (1995), Wagner and Deller (1998), and Chandra (2002).

In literature, growth is measured by an increase in output in the long-run and this measurement is accepted by researchers with not disagreement. Growth measured this way is considered favorable to the economy in any case.

3. Instability Literature

Short-run fluctuations were seldom addressed within growth models until the 1980s (Aghion & Howitt, 2009). The real business-cycle researchers expanded the neoclassical model and viewed such things as productivity shocks (short-run fluctuations) as a main source of persistent fluctuations (long-run growth path) (Kydland and Prescott, 1982; Long and Plosser, 1983).

The Harrod-Domar model was also revised and expanded by other scholars. Frankel (1962) included substitutable factors and knowledge externalities in the model, Romer (1986) added the concept of intertemporal consumer maximization to the model, and Lucas (1988) emphasized the role of human capital accumulation in creating and delivering knowledge. Jones, Manuelli, and Stacchetti (2000) explained the impact of volatility on growth, using the AK framework's assumptions that growth depends on capital accumulation and technological advance may offset diminishing returns to capital. They assert that the consumption depends on the random productivity shock and that the expected growth rate depends on the equilibrium ratio of savings to consumption, determined by individuals' utility maximization function. If the elasticity of marginal utility is less than 1.0, an increase in volatility reduces expected growth by reducing the risk-adjusted return on investment and discouraging savings. If it is greater than 1.0, on the other hand, a rise in volatility increases expected growth through increasing precautionary savings. The households' elasticity of intertemporal substitution, $e = 1/\sigma$ where σ is the elasticity of marginal utility, determines which of the two effects dominates (Phelps, 1962; Jones, Manuelli, & Stachetti, 2000). Aghion and Howitt (2009) demonstrate that this elasticity of substitution is less than one in most countries based on aggregate consumption

studies. Thus, the AK approach supports positive correlations among volatility (i.e., shortrun fluctuations), aggregate **savings**, and long-run growth.

Based on the Schumpeterian model, Aghion, Angeletos, Banerjee, and Manova (2010) explore the relationship between growth and volatility. In determining volatility, aggregate productivity is assumed to fluctuate around a knowledge level. In determining growth, they first assume that two-period lived entrepreneurs comprise a nation's economy. Each entrepreneur is given an initial wealth proportional to their knowledge level. Each entrepreneur allocates his or her initial wealth between short-run capital investments and long-run productivity-enhancing investments such as research and development, information technology equipment, and organizational capital. Each of the two types of **investments** is considered as a substitution for the other, and only the long-run investments are assumed to contribute to long-run growth.

Under these assumptions, they assert that the existence of **credit constraints** determines the direction and degree to which long-run growth and short-run volatility are correlated. In the absence of credit constraints, returns to long-run productivity-enhancing investments are less procyclical than returns to short-run capital investments. Conceptually, demand for manufactured goods is lower in recessions; the return to short-run capital investments is lower in recessions; the opportunity cost of long-run productivity-enhancing investments is lower in recessions; thus, long-run productivity-enhancing investments may increase in recessions. In the absence of credit constraints, it is possible for short-run volatility to have a growth-enhancing effect. Under credit constraints, however, firms earn less in recessions; firms' ability to borrow reduces in recessions affecting innovation; firms invest more in short-run capital than long-run productivity-enhancing investments as quick

returns or visible outcomes lead to the firms' survival; and thus, long-run productivityenhancing investments are reduced in recessions, resulting in a damaging effect of volatility on growth. In sum, economies that are more financially constrained experience a more negative correlation between volatility and growth.

Acemoglu and Zilibotti's (1997) stochastic model, based on a portfolio framework, calls attention to the diversification of activities. The premise of this model is that more economic activities lead to less volatile economies. According to this model, every economic activity involves a fixed cost. Therefore, an economy under relatively heavy financial constraints must have relatively fewer activities. This inability to diversify the number of activities results in a higher risk, which forces economies to adopt risk-averse technologies, even if those technologies are inferior in productivity. As a result, the stochastic model concludes that more financially constrained economies experience higher volatility when facing shocks. The stochastic growth model classifies an economy's stages of financial development and differentiates the impact of macroeconomic policy on longrun growth at various stages. Based on the assumption that each economic activity involves a fixed cost, economies at an early stage of development can only finance a limited number of activities. The ability of such economies to diversify is limited, so safer, but inferior technologies are preferred. As a result, growth is slower and more volatile at the early stages and stabilizes at later stages of development.

Volatility is measured in literature by a variance or a percent change from a preceding value. Unlike growth, which is deemed good to any economy, volatility is considered favorable or unfavorable depending on the set of circumstances in which the

economy is situated. This double-edged sword seems to originate in large part from the inclusion of both increases and decreases in the measurement of volatility.

4. Resilience Literature

The concept of resilience began with Holling (1973) who defines resilience as "a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist." Since then, resilience has appeared in a variety of fields ranging not only from ecology but to psychology (Bonanno, 2004; Bonanno & Mancini, 2008), business (Sheffi, 2005), and economics (Dhawan & Jeske, 2006; Hill, Wial, & Wolman, 2008; Rose, 2004; Rose, 2009). Urban planners and regional economists also address resilience (Burby, Deyle, Godschalk, & Olkshansky, 2000; Godschalk, 2003; Pendall, Foster, & Cowell, 2009; Swanstrom, Chapple, & Immergluck, 2009; Hill et al., 2010).

The broad use of the term confirms a wide interest in the general concept, but also results in various definitions and measurements. Terms similar and/or related to resilience contribute to discrepancies in definitions (Rose, 2009; Norris, Tracy, & Galea, 2009), which include stability, sustainability, mitigation, resistance, adaptation, and recovery. Discrepancies also result from how researchers identify a period of interest in which to study resilience. Some researchers consider pre-, in-, and post-disruption together and define actions in this entire period as part of resiliency efforts (Bruneau et al., 2003; Godschalk, 2003). Other researchers, such as Rose (2009), however, emphasize disruption periods only and limit actions that occur during the disruption as resiliency efforts. In effect, almost all resilience researchers tend to start their discussion by pointing out the

lack of an agreed definition, using words like fuzziness, ambiguity, and vagueness. Such a wide use of the term is even criticized to have led to the dilution of the original ecological meaning, the reduced applicability in ecological science, and the prevention of the progress of resilience theory (Brand & Jax, 2007).

When Holling used the term "resilience," he limited it to the speed of return to a pre-shock status after disturbance. The pre-shock status was assumed to be a single equilibrium that exists in the system. This assumption was later weakened, and the possible existence of multiple equilibria was proposed. In such a system, more diverse and complex pictures of an economy were considered as a type of resilience. The term further expanded to contain the reactions that contribute to the return. Like the development of growth theories, the definition of resilience has been developed in a way that it includes additional aspects of the reactions to shocks. This evolutionary track has broadened the scope from engineering to ecological to adaptive explanations that result in a more expansive description than that Holling originally intended.

Efforts to clarify and categorize the concepts were since made by several researchers (Martin & Sunley, 2015). Pendall, Foster, and Cowell (2009) proposed three frameworks underlying resilience. The first is based on a single equilibrium system where returning to the pre-existing stable equilibrium after experiencing a disturbance is considered resilience, called "engineering resilience" by Holling (1973). How quickly a system returns to the equilibrium is the main interest in this approach. This way of understanding is prevalent in ecology, psychology (Bonanno, 2004), and disaster studies (Vale & Campanella, 2005). For example, resilience may imply a stable physical and mental health for an individual who experienced the death of a family member or a previous

growth trajectory achieved by a city that suffered from an earthquake. This framework is linked to the discussion of self-restoring equilibrium dynamics in economics (Martin & Sunley, 2015). The second is based on a multiple equilibria system in which shifts to new equilibria are possible and may be understood as resilience. This concept is helpful to the economics literature in which multiple equilibria theories have been expanded recently. Lastly, under a complex adaptive system, the focus is on interactions and feedbacks of the system's elements that make the system more or less resilient.

Despite disagreement about the specific definitions, the underlying concept is an individual's or a group's ability to recover from a disruption. Resilience is always deemed favorable to the economy regardless of specific definitions. In this study, resilience is defined as the speed with which a region is able to successfully rebound from an economic downturn (i.e., return to its pre-downturn level). How this conceptual definition is realized in empirical research on regional economic dynamics follows.

Research has demonstrated that the national recessions affect regions differently. Carlino and Sill (2001) performed trend/cycle decompositions on regional real income and concluded that there is considerable divergence of regional business cycles from national cycles. Wilkerson (2009) conducted a comparison of the twelve districts of the Federal Reserve System's performances against the national recessions by using state level quarterly employment data from 1957 to 2003. He found that most districts entered downturns at a different time than the national recession defined by NBER over the past eight recessions and that the percentage of employment change during recessions and expansions also greatly differed by districts. He noted that those who underperform the nation in one recession tend to underperform the nation in other recessions and vice versa, suggesting that some factors may relate to all recessions. Another finding is that milder recessions tend to produce greater variation in the timing of entry and exit among districts, which indicates that milder recessions have been more regionalized. The variation in the entry timing is found to be greater than that in the exit timing, and the exit timing is more uniform from deep recessions than mild ones. The national monetary and fiscal policy supports are greater in deep recessions and those supports are made to all regions around the same time (Wilkerson, 2009; Carlino & Defina, 1998; Fratantoni & Schuh, 2003; Wilson, 2009). Lastly, Wilkerson found the existence of non-national recessions, defined by more than one consecutive quarter of job losses, in some districts. Owyang et al.'s (2005) reached the same conclusion that the timing and depth of the recessions differ by state, by examining the seven states within the Eighth Federal Reserve Districts (Arkansas, Illinois, Indiana, Kentucky, Mississippi, Missouri, and Tennessee) during the 1990 and 2001 recessions. Henderson and Akers (2009) focused on rural versus urban areas and determined that rural areas suffer less than urban areas and that the housing and financial crisis was less severe in rural areas.

Grobar (1996) conducted qualitative case studies of New England and Southern California for the late 1980s and early 1990s, finding that the causes of recessions differ by region. In an effort to examine the nature and possible causes of the variation in the impact of and response to downturns among regions, researchers have conducted empirical studies on business cycles. The most frequently stated cause is the diversification of economic activities. Chandra (2002), using Bureau of Economic Analysis and Rappaport data sets on Gross State Product over the periods 1977-1996 and 1963-1992 for the all states in the United States, tested if the portfolio view of economic growth still applies. Through stochastic frontier estimation, Chandra confirmed that more diverse state economies tend to be more stable, which supports the portfolio framework. Other researchers empirically tested a portfolio framework at the regional level. Using total employment in the manufacturing industry in Canada from 1976 to 1997 and applying cross-sectional analysis and first-difference analysis, Baldwin and Brown (2003) identified that regions with higher industry-diversity indexes, lower-than-average growth rates, larger plant sizes, and higher export intensities tended to be more stable. They asserted that the impact of diversity and export intensity on regional volatility differed with the economic size of the regions with volatility greater for smaller regions.

A region's specific industrial composition is also believed to be another cause for variation. Wilkerson (2009) claimed that unique industrial structures of regions cause the variation in the depth of recessions and the timing of economic recoveries. Garcia-Mila and McGuire (1993) examined the relationship between a state's industrial mix and the growth rate and variability of the state's economy. By using annual employment data from 1969 to 1985, they concluded that higher shares of construction and FIRE (finance, insurance, and real estate) industries during this period contributed to higher growth rates for states, whereas the manufacturing industry contributed to higher variability in state economies. Their study acknowledged that a state's resilience is attributable to industrial mix.

The list of causes has expanded over time. Connaughton and Madsen (2009) conducted a regression analysis of the 2001 recession using several demographic and economic measures as independent variables and every state's contribution to the overall U.S. Okun gap (the relationship between growth and employment) as the dependent

variable. They concluded that some factors increased a state's economic volatility, while others increased a state's resilience. Further, they concluded that the percentage of a state's adult population with a four-year college degree and the percentage employed in manufacturing were the two most critical factors in determining the variability in the size of the relative Okun gap contribution. By applying a factor analysis to state level quarterly personal income and employment data for 1990 through 2006, Owyang, Rapach, and Wall (2009) decomposed the economic dynamics into three factors: the national business cycle, the dissonance between personal income growth and employment growth, and the nominal returns. They examined the relationships between each state's two data series (income and employment growth) and the three national factors. They examined using spatial Durbin models how closely state economies move with the national business cycle factor. Though they did not use the term, stability or resilience, they viewed that when states more closely followed the national business cycle, their economies fluctuated more. They claimed that agglomeration, measured by establishment density and urban population share, played a role that was as important as that for a state's industrial mix. They asserted that the large labor pool available in major urban agglomerations led to a flexible and efficient match of workers, which resulted in prompt, positive reactions to economic fluctuations. Henderson and Akers (2009) claimed that strong commodity prices had maintained farm incomes, resulting in a less severe housing and financial crisis in rural areas.

Hill et al. (2010) conducted a metropolitan level analysis using annual total employment for the period 1978-2006 for 361 metropolitan statistical areas in the United States. They first specified three types of shocks: (1) A national economic shock occurs when the national growth rate declines by more than 2.0 percentage points from its annual

growth rate over the previous eight years. (2) A local industry shock occurs when the region's expert industries experience a job loss of more than 0.75 percent of total regional employment. An export industry is defined as that whose share of regional employment is at least one percent and is at least 80 percent above the same industry's share of national employment. (3) A national industry shock occurs when the local industry downturn exists and simultaneously an industry responsible for the biggest job loss in export base experienced a decline of national annual employment growth rate by more than 2.0 percentage points from its national eight-year growth rate. They then defined a downturn as a decline of more than 2.0 percentage points from the annual regional growth rate over the previous eight years, in the year of the shock or the year thereafter. If the eight-year growth rate was 4.0 percent or higher, the region's growth rate had to decline by more than half of the previous growth rate. A region was considered resilient if its annual growth rate returns to the pre-downturn eight-year growth rate within four years. Using a logistic regression model, they found that a higher share of the economy's population with no college background, a higher share of employment in durable manufacturing, and the existence of Right to Work laws made metropolitan areas more resilient to shocks. These characteristics were deemed to reduce the amount of time it took the region to become resilient following a regional economic downturn.

Landis (2014) used the rate of job change by MSA, the rate of gross metropolitan product change, and changing unemployment rates between 2007 and 2012 to classify 193 largest metropolitan areas into five categories. He split the study period into downturn (2007-2009) and recovery (2009-2012) periods and classified each metropolitan area based on these three measures compared to the national figures. The five categories were 1) those

that performed similar to the nation in both periods; 2) those that underperformed the nation in both periods, 3) those that outperformed the nation in the first half and underperformed in the latter half, 4) those that underperformed the nation in the first half and outperformed in the latter half (resilience), and 5) those that outperformed the nation during both periods (robustness). He attempted to identify variables associated with resilience or robustness using multinomial logit models. He found that higher shares of manufacturing employment and fewer airline passenger enplanements were positively related to resilience or robustness in terms of employment and gross metropolitan product. Ordinary logit models revealed that higher levels of educational attainment were positively related to employment, gross metropolitan product, and unemployment rate resilience or robustness.

Existing research demonstrates that the extent to which a regional economy grows resiliently varies by region and identifies some factors that are associated with this variation. These studies have two major tendencies in their research design. First, studies show variations in their definitions for central concepts such as growth, downturn, recession, recovery, and resilience across studies, and need a more technical definition for these concepts. The relatively newer term, resilience, in particular is not free from author-defined arbitrary periods in the estimation. This complexity and variation in the definition are why the literature characterizes resilience as a concept that is fuzzy, unclear, and underdeveloped. Second, almost all of the studies emphasize how regional economies react to "national" recessions defined by the NBER, ignoring the variation in time of shock across regions and the existence of non-national, purely local downturns. To account for the variation in time of national shock across regions, some researchers create their own definitions for national recessions. An author-defined timeframe, such as two years prior

to the start of the national recession and two years after the end of the national recession, is often used to allow for some variation across regions in the timing of entering and existing national recessions. Although such timeframes tend to be based on other research, their length vary across studies and, more importantly, regional economies' vacillations outside the given timeframe are excluded from analyses under this structure. These two tendencies deliver a meaningful information on regional dynamics surrounding the national business cycle, but a more simplified definition without any author-defined arbitrary in calculation would lead to a more generalized understanding of regional reactions to economic ups and downs.

What further research is expected to contribute is to develop a measure with more generalizability and better comparability. This study proposes crystallized definitions of growth, stability, and resilience that are more straightforward and are applicable directly to other times, units of analysis, or geographies.

On another note, given the labor market coherence of MSAs and the increasing focus of public finance and planning on metropolitan governance, it is surprising that few studies have been conducted at the MSA level, but rather on a broader geo-political scale. In addition, to my knowledge, no study provides a comprehensive analysis of explanatory factors discussed in theoretical and empirical literature at a subnational level to enable a better understanding of which is most critical from a practical perspective. This study's comprehensive investigation with a focus on metropolitan level economic dynamics may add to the existing literature.

CHAPTER 2. PROPERTIES OF GROWTH, STABILITY, AND RESILIENCE

1. Data and Methods

This study suggests crystallized definitions of growth, stability, and resilience, which will be used for the rest of the analyses. Growth is a term that has been widely used in the literature on regional economics and urban planning. Conceptually, growth is defined as "the increasing capacity of a geographical entity to improve the quantity and quality of goods and services." and researchers tend to concur on this definition with respect to regional economies. Thus, this study defines *growth* as the compound annualized growth rate of MSA monthly total employment from January 1990 to March 2017. The higher the measure of growth, the faster an MSA grows. Growth of an MSA is

$$Growth = \left(\frac{x_T}{x_1}\right)^{\frac{12}{T-1}} - 1$$

where x_1 is the number of total employees at the first month of the study period, January 1990; x_T is the number of total employees at time *T*; and *T* is the last month of the study period, March 2017.

Stability is defined as "a geographical entity's ability to maintain its initial economic condition under small fluctuations" in the literature on regional economics. Low standard deviation from the trend line or the mean has been a common representation of stability in analyses. I examine *instability* rather than stability, per se. Here *instability* is defined as the average share of pre-downturn total employment that was lost during economic downturns and recoveries. A *downturn* is defined as the elapsed time between a

peak and a trough. A *recovery* is the period between a trough and the return to the previous peak (i.e., the start of a downturn). Lost employment is estimated by adding the difference between a previous peak employment (i.e., an employment at the start of a downturn) and an actual employment for all downturn and recovery months. Expected employment is estimated by adding an actual employment for non-downturn and non-recovery months and a previous peak employment for downturn and recovery months. Consequently, the less employment is lost after the start of the downturn, the lower the measure of instability, which indicates a more stable economy. Instability of an MSA is

$$f(x) = \begin{cases} x_{pi}, & x_{pi} > x_t \\ x_t, & x_{pi} \le x_t \end{cases}$$

 $g(x) = x_t$

Instability =
$$\left(\int_{1}^{T} f(x)dx - \int_{1}^{T} g(x)dx\right) / \int_{1}^{T} f(x)dx$$

where x_t is total employees in an MSA at time *t*; *t* ranges from 1, January 1990, to *T*, March 2017; x_{pi} is total employees in an MSA at a preceding peak (i.e., the starting month of an *i*th downturn); and *i* is the period of a downturn and a recovery that an MSA experiences for the study period, which ranges from 1 to m times. For an MSA that fails to return to its pre-downturn employment, *i* denotes the period of a downturn without recovery.

The reason for using the employment level at a preceding peak for the estimation of expected employment is to maintain an objective and conservative view on expected employment. One may imagine a trendline as an alternative standard, but its slope depends on how many periods are selected by an author, leaving subjectivity within the instability index. Furthermore, in the U.S. where the size of a labor market increases over time in most metropolitan areas, an expected employment is overestimated by a trendline, which can be an aggressive and hence less realistic goal for a period of downturn and recovery.

Based on the common concept in the literature that resilience is an individual's or a group's ability to rebound from a disruption, I define *resilience* as the average relative speed with which an MSA recovers from a trough to a pre-downturn level of employment. Specifically, resilience is the length of time needed for an MSA to return to its predownturn employment level, but conditioned on the depth of the economic trough. An MSA is considered resilient if it returns relatively rapidly to its pre-downturn employment levels. The way in which resilience is defined here, the speed of recovery, is critical especially in preventing a double dip. If a metropolitan area does not recover rapidly from a local downturn or national recession, it is likely to encounter the next national recession while in the not-yet-recovered status, resulting in a severer employment loss. St. Louis MSA, MO-IL, for example, faced the 2007-2017 recession when they were still recovering from the 2001-2007 recession. The double dip aggravates their suffering labor market.

Resilience is measured in terms of an annual rate using monthly data. The mathematical expression is as follows:

$$Resilience = \frac{\sum_{i=1}^{m} w_i \left(\left(\frac{x_r}{x_n} \right)^{\frac{12}{(r-n)}} - 1 \right)_i}{\sum_{i=1}^{m} w_i}$$

where x_r is total employees at the time of recovery; r is the time of recovery; x_n is total employees at the time of nadir; n is the time of nadir; i is the number of recovery periods an MSA experiences during the study period, which ranges from 1 to m times; and w is the weights.

Given these definitions, I seek to discover how MSAs have performed in terms of instability and resilience since 1990. The *Quarterly Census of Employment and Wages (QCEW)*, available through the Bureau of Labor Statistics (BLS) from January 1990 to March 2017,² is the main data source used here. QCEW data include monthly employment by county for the entire United States. The data include employment covered by State Unemployment Insurance laws and the Unemployment Compensation for Federal Employees program only. Thus, it omits military, self-employed workers, proprietors, some domestic workers, and railroad workers under the railroad unemployment insurance system.

I applied the X-13ARIMA-SEATS program, a seasonal-adjustment program software provided by the Census Bureau, to each of the 382 monthly metropolitan area series available from the QCEW to adjust seasonal fluctuations and capture the core pattern

² Due to availability of the North American Industry Classification System (NAICS) based data, the study period begins January 1990. Although this research does not use official national recessions in the analysis, this timeframe includes the three most recent official recessions determined by the National Bureau of Economic Research. Total employment is used to measure the three measures, growth, instability, and resilience. The monthly employee counts are reconstructed to metropolitan level data by authors based on the delineations of Metropolitan Statistical Areas, published by the Office of Management and Budget (OMB) on July 15, 2015. The delineations reflect the OMB's 2010 Standards for Defining Metropolitan and Micropolitan Statistical Areas published on June 28, 2010. In the 2010 Standards, a Metropolitan Statistical Area (MSA) is defined as a geographical entity that includes at least one urbanized area of 50,000 or more population and its outlying counties with strong social and economic connection to the urbanized area as measured by commuting and is delineated in terms of whole counties and equivalent entities. The delineations include 382 MSAs in the United States and 7 MSAs in Puerto Rico. The 389 MSAs include approximately 85 percent of the U.S. population. Of the delineated 389 MSAs, those in Puerto Rico are eliminated for this study to exclude those that have disparate administrative and economic conditions. Consequently, data for this study are limited to 382 MSAs in 50 states and District of Columbia. The data were retrieved from http://www.bls.gov/cew/datatoc.htm on September 25, 2017.

of changes. Under the X-11 seasonal filter, seasonal, calendar, and irregular components were extracted from the original series, resulting in the trend-cycle component. I used the trend-cycle data to measure each MSA's growth, instability, and resilience for the study period and tracked it to enable classification into the eight categories shown in Figure 1.

2. Results

Using the trend-cycle data, growth, instability, and resilience measures are estimated for each of the 382 MSAs for a pooled period of 327 months based on the formulas provided in Section 3. Consequently, three values are assigned to each MSA for growth, instability, and resilience. In exceptional cases, resilience cannot be calculated using the formula provided and zero is assigned as the measure of resilience. This occurs when an MSA's employment decreased during the analysis period and never returned to its pre-downturn level. Four MSAs are assigned zero for their resilience indices. Descriptive statistics of the data (i.e., 124,914 monthly observations) are shown in Table 1.

Variables	Mean	Standard Deviation	Minimum	Maximum
Monthly Employment	283,175	666,356	5,548	9,291,358
Monthly Employment (Seasonally Adjusted)	283,222	666,404	5,966	9,178,035
Growth	0.0113	0.0090	-0.0107	0.0569
Instability	0.0259	0.0226	0.0008	0.1444
Resilience	0.0235	0.0226	0.0000	0.3955
Frequency of Downturns	8	3	1	18

Table 1. Descriptive Statistics of Core Variables

The simple mean MSA annual growth rate 1.13% is comparable to the nation's weighted average annual MSA growth rate of 1.05%.³ But means of the other two indices (0.0259 and 0.0235) are twice as high as their national equivalents (0.0113 and 0.0144, respectively), which implies skewed distributions and begs for future research in their own rights. These descriptive statistics also show that MSAs experience very different counts of downturns during the study period, ranging from 1 to 18,⁴ suggesting that each MSA's economy, indeed, has a unique path.

Table 2. Correlation Coefficients

	Growth	Instability	Resilience	Freq. of Downturns
Growth	1			
Instability	-0.4918	1		
Resilience	0.1224	0.2852	1	
Frequency of Downturns	0.2815	-0.4371	0.0613	1

Correlations show that while they are related, the three are, statistically speaking at least, separate dimensions since the absolute value of no correlation peaks above 0.5. I next ranked the MSAs by each index. Better performing MSAs are assigned best rankings in all three indices. That is, the most rapidly growing MSA is ranked first and the MSA with the lowest compound monthly growth rate is ranked last at 382. Likewise, 1 is assigned to the most stable MSA—the one with the lowest instability index—and a rank of 382 is assigned to the most unstable MSA. An MSA with the highest resilience index is ranked first and an MSA with the lowest value is assigned a rank of 382. Therefore, the better the rank of an MSA, the better it has performed on each dimension since 1990. Four MSAs that never

³ Nationwide indices are calculated by adding total employment of the 382 MSAs and applying the equations addressed in the methods section. Employment outside the 382 MSAs, such as that on micropolitan statistical areas or rural areas, is not considered.

⁴ The metropolitan U.S. experienced three downturns during the study period based on this measure.

returned to the pre-downturn employment level after a downturn do not have a valid number for their resilience index and therefore a resilience rank of 379 is assigned to these MSAs. Table 3 below identifies the top ten and bottom ten MSAs by growth rate, along with their values and rankings for the other two indices. It also shows the number of downturns. MSAs with similar growth rates do not necessarily have similar levels of stability or comparable levels of resilience. In particular, stability for the top ten and resilience for the bottom ten almost run the gamut from minimum to maximum levels. This further confirms the variation in growth patterns amongst MSAs.

Metropolitan Statistical Area	Growth		Instab	Instability		ence	Freq. of Downturns
	Index	Rank	Index	Rank	Index	Rank	
The Villages, FL	0.0569	1	0.0169	167	0.1046	2	14
St. George, UT	0.0558	2	0.0303	274	0.0457	19	3
Daphne-Fairhope-Foley, AL	0.0367	3	0.0126	120	0.0255	111	7
Las Vegas-Henderson-Paradise, NV	0.0364	4	0.0324	288	0.0296	66	3
Austin-Round Rock, TX	0.0350	5	0.0069	46	0.0306	57	3
Bend-Redmond, OR	0.0346	6	0.0341	296	0.0366	35	7
Provo-Orem, UT	0.0338	7	0.0130	126	0.0339	42	4
Coeur d'Alene, ID	0.0333	8	0.0252	240	0.0385	29	6
Laredo, TX	0.0322	9	0.0058	34	0.0304	59	11
McAllen-Edinburg-Mission, TX	0.0321	10	0.0008	1	0.0184	224	9
Springfield, OH	-0.0033	373	0.0889	372	0.0294	69	5
Rocky Mount, NC	-0.0037	374	0.0665	356	0.0316	50	6
Youngstown-Warren-Boardman, OH-PA	-0.0044	375	0.0788	366	0.0353	37	6
Elmira, NY	-0.0047	376	0.0782	364	0.0203	193	5
Pine Bluff, AR	-0.0049	377	0.0565	348	0.0140	305	6
Mansfield, OH	-0.0060	378	0.0794	368	0.0293	71	7
Binghamton, NY	-0.0060	379	0.0850	370	0.0000	379	1
Danville, IL	-0.0063	380	0.0790	367	0.0283	80	3
Flint, MI	-0.0083	381	0.1444	382	0.0302	60	2
Weirton-Steubenville, WV-OH	-0.0107	382	0.1046	377	0.0000	379	1

Table 3. Top Ten and Bottom Ten Metro Areas According to Growth Rates

MSAs with the highest growth rates tended to be in southern states or in contiguous western states. Declining MSAs tend to be in East North Central Census Division and nearby states. The Villages, Florida, and St. George, Utah, have comparable growth rates for the study period, suggesting they could be good subjects for a case study into a deeper investigation of what enabled them to grow so rapidly. The analysis reveals that only a few of the top ten MSAs were fairly stable. In particular, those in Texas were relatively stable, but the remaining seven of the top ten growing MSAs were not. This suggests that instability may sometimes be a necessary evil for economies to grow quickly and at the same time that Texan economies are remarkably stronger in both growth and instability aspects.

At least at first glance, resilience, appears to be more strongly associated with longterm growth given economic volatility. This makes sense since resilience does reflect the ability to grow beyond the recovery point in the aftermath of a downturn. That is, it is more clearly growth-related. The Villages, Florida; St. Georges, Utah; and Coeur d'Alene, Idaho, are exemplary MSAs in this category. Among those with the lowest growth rates, a comparison of the three indices identifies those with potential to recover despite their current declining status. Youngstown-Warren-Boardman, Ohio-Pennsylvania, and Rocky Mountain, North Carolina, rank 37th and 50th in resilience, indicating a higher probability of returning to their pre-downturn status than that for other declining MSAs.

Overall, this table suggests that stability and resilience vary greatly amongst MSAs, even if they have similar growth rates. These findings further indicate that the traditional concept of growth, the overall growth rate, itself masks the more complicated dynamics of growth. It also confirms that a more sophisticated examination of growth trends is needed to identify the make-up of a healthy regional economy. Median growth, instability, and resilience are compared with each MSA's values to classify them into the eight categories of the cube shown in Figure 1. In Table 4, I indicate how many MSAs during the study period belonged to each category. It turns out that MSAs are largely polarized and mostly belong to the "best" and "worst" categories. But, not surprisingly, MSAs of the U.S. Northeast—the nation's old industrial core tended to grow slowly and those in the "newer" West region grew more quickly. Midwest MSAs, meanwhile, are characterized either by the combination of fast growth and stability or by slow growth and instability. MSAs of the South dominate fast-growing categories but some appear in slow-growing categories too. This suggests that while a diversity of economic causes may be at play within the South and the Midwest, the Northeast and the West may be growing through similar forces (perhaps internationally related).

Metropolitan Statistical Area		Northeast	Midwest	South	West	Total
Growing fast, stable, resilient	Count	0	3	39	26	68
	Percent	0.00	4.41	57.35	38.24	100.00
	Count	1	25	26	14	66
Growing fast, stable, non-resilient	Percent	1.52	37.88	39.39	21.21	100.00
Counting fort anotable molilient	Count	0	2	21	25	48
Growing fast, unstable, resilient	Percent	0.00	4.17	43.75	52.08	100.00
Growing fast, unstable, non-resilient	Count	0	1	2	6	9
	Percent	0.00	11.11	22.22	66.67	100.00
	Count	3	8	3	0	14
Growing slowly, stable, resilient	Percent	21.43	57.14	21.43	0.00	100.00
Consistent alterative attaching and an antility of	Count	13	8	17	5	43
Growing slowly, stable, non-resilient	Percent	30.23	18.60	39.53	11.63	100.00
Crowing slowly, unstable resilient	Count	7	22	26	6	61
Growing slowly, unstable, resilient	Percent	11.48	36.07	42.62	9.84	100.00
Growing slowly, unstable, non-resilient	Count	24	24	22	3	73
	Percent	32.88	32.88	30.14	4.11	100.00
	Count	48	93	156	85	382
Total	Percent	12.57	24.35	40.84	22.25	100.00

Table 4. Regional Distribution of Metro Areas Categorized by Median Indices

As expected, MSAs that fall into the same category tend to share similar patterns. MSAs from the South and West are overrepresented in the first category in Table 4 (growing fast, stable, resilient). The South has 57% and the West 38%, when they comprise 41% and 22%, respectively, nationwide. Texan and Californian MSAs drive such a Southern and Western dominance. Of the full set of 24 Texas MSAs, 10 regions fall into this first category. Eight of the full set of 26 Californian MSAs belong here. As a side note, this group also contains an inordinate number of MSAs that contain state capitals or a state's largest city. Eighteen out of 72 of such MSAs belong to this best performing category and are over-represented (27% versus 19% nationwide). Atlanta-Sandy Springs-Roswell, Georgia; Nashville-Davidson-Murfreesboro-Franklin, Tennessee; Austin-Round Rock, TX; and Seattle-Tacoma-Bellevue, WA are examples of such MSAs in this category. MSAs in the second category (growing fast, stable, non-resilient) are fairly well represented across the nation's geography, with the exception of the Northeast and an increased showing from the Midwest. A majority (7) of the remaining Texan MSAs belongs to this category. Of the 11 MSAs in Washington State, 5 are included here, or 36% of the category's 14 western MSAs.

The third category (Growing fast, unstable, resilient) is comprised of mostly MSAs from the South (44%) and West (52%). Closer examination reveals that most of this category's southern MSAs are concentrated in Florida (14 out of the full set of 22 MSAs in Florida) and that Californian MSAs are well represented here (7 out of 26 MSAs in California). The composition of the fourth category (Growing fast, unstable, non-resilient) is mostly Western MSAs, which are dispersed across states. This category contains only 9 MSAs in total, which is the smallest out of the eight categories.

MSAs that fall into the fifth category (Growing slowly, stable, resilient) are spread throughout the nation with none from the West regions. The total count of MSAs in this category (14) is also very low, indicating that it is rare to be characterized either by a combination of stability and resilience or that of instability and non-resilience simultaneously, regardless of growth status. The sixth category (Growing slowly, stable, non-resilient) is also more heavily populated by MSAs from the Northeast and less so from MSAs of the Midwest and West. Of the 13 MSAs in the Northeast that belong to this category, 10 are in Pennsylvania. In addition, MSAs with capitals or the largest city in a state, such as Philadelphia, Pennsylvania; Albany, New York; and Baltimore, Maryland dominate (28% compared to their overall share of 19%). Coupled with the high representation of such MSAs in the first category, it confirms that such MSAs tend to be characterized by being stable regardless of their growth and resilience tendency. Another implication is that not all larger MSAs grow more slowly or less resilient. I have surmised that it is tougher for economically larger regions to grow more quickly without radical industrial shifts and that larger regions have a more complex economic system and, hence, less responsive to shocks. However, the dominance of large metros in both the first and sixth categories suggest that the size of the economy itself is not a determining factor for the difference in growth and resilience.

Those that grow slowly, are unstable, but resilient are dispersed throughout the nation with a slightly low representation from the West. Less populated MSAs in Pennsylvania such as Gettysburg and Erie form most of the 11 MSAs in the Northeast that are classified into this group. Of the 6 MSAs in the West that are classified into this group, 4 are in California, including the San Francisco Bay area, San Jose-Sunny Dale-Santa Clara,

and Santa Cruz-Watsonville. Those with capitals or the largest city in a state tend not to be in this category, as only 3 of 72 such MSAs in the nation belong here (5% versus 19% nationwide). Ohio shows a higher share here (8%) than their nationwide figure (3%). The last category (Growing slowly, unstable, non-resilient), essentially the MSAs performing badly on all measures, shows relatively high representation from the Northeast, including Boston, greater New York City, and Bridgeport-Stamford-Norwalk, Connecticut. New York State, in particular, contains one third of such Northeast MSAs. The Midwest MSAs are also over-represented here and a vast majority is from Michigan. Nine out of 15 MSAs in Michigan belong to this category. The MSAs from the West are all in California, which include the Los Angeles Basin; Santa Maria-Santa Barbara; and Redding.⁵

If I classify the MSAs on the three measures using national metropolitan average values in lieu of medians, I obtain somewhat different results. For example, the concentration of MSAs with a state capital or the largest city in a state between the category of "fast growth, stability, and non-resilience" and the category of "slow growth, stability, and non-resilience" is still valid in terms of their shares. Due to the decreased total count in these categories in general, however, the counts of such MSAs are now 5 (previously 14) and 3 (previously 12). Instead, sixteen of such MSAs now belong to the category of "fast growth, instability, and resilience" (previously 4) and 15 are in the category of "slow growth, instability, and resilience" (previously 3), increasing their shares in these categories by two and three times, respectively. The dominance of Texan MSAs in the first category, Florida and Californian MSAs in the third group, and Michigan, Ohio, and Northeast MSAs in the seventh and eighth categories is retained, although the degree of

⁵ A complete list of MSAs in each category in provided in Appendix A with their values, rankings, and the number of downturns.

concentration is not identical. Still, it seems using national metropolitan averages rather than medians as cut-offs yields an even more polarized distribution of MSAs. Fewer regions are now classified as "stable" (sliding from the natural split at 191 to just 100) and more are identified as resilient (from the natural split at 190 to 245), while the growth index distributes regions similarly (from the natural split at 191 to 202).

The upshot of the above transitions is that an increased share of MSAs falls into either the third or the seventh categories (Growing fast, unstable, resilient and Growing slowly, unstable, resilient), while still high shares are retained by the first and the eighth categories as shown in Table 5. Of the 382 MSAs 106 is the count of that are classified as Growing fast, unstable, resilient as well as 111 being classified as Growing slowly, unstable, resilient.

Metropolitan Statistical Area		Northeast	Midwest	South	West	Total
	Count	0	16	35	20	71
Growing fast, stable, resilient	Percent	0.00	22.54	49.30	28.17	100.00
Council of the stable man and ilingt	Count	0	7	7	1	15
Growing fast, stable, non-resilient	Percent	0.00	46.67	46.67	6.67	100.00
Crowing fact unstable regilient	Count	1	11	45	49	106
Growing fast, unstable, resilient	Percent	0.94	10.38	42.45	46.23	100.00
	Count	0	2	6	2	10
Growing fast, unstable, non-resilient	Percent	0.00	20.00	60.00	20.00	100.00
Crowing clowly stable resilient	Count	2	1	1	2	6
Growing slowly, stable, resilient	Percent	33.33	16.67	16.67	33.33	100.00
Crowing slowly stable non resilient	Count	4	0	4	0	8
Growing slowly, stable, non-resilient	Percent	50.00	0.00	50.00	0.00	100.00
Growing slowly, unstable, resilient	Count	21	39	42	9	111
Growing slowry, unstable, resilient	Percent	18.92	35.14	37.84	8.11	100.00
Crowing slowly unstable non resilient	Count	20	17	16	2	55
Growing slowly, unstable, non-resilient	Percent	36.36	30.91	29.09	3.64	100.00
Total	Count	48	93	156	85	382
10(a)	Percent	12.57	24.35	40.84	22.25	100.00

Table 5. Regional Distribution of Metro Areas Categorized by Average Indices

Using the measures, I next mapped the MSAs to observe geographical clustering. For mapping purposes, the measures were cut on quintiles, which were assigned graduated colors. Darker colors indicate better the performance in all maps. MSAs that grew fast, were stable, and were resilient were assigned the darkest color.⁶ Figure 2 indicates Southwest, Texas, and Florida MSAs grew faster than those in the Northeast since 1990. A few large MSAs located in California, Nevada, Arizona, as well as those in Utah performed outstandingly. Amongst the fastest-growing MSAs, those in Texan regions and a few MSAs in the Midwest remain stable, as shown in Figure 3. When the fastest-growing regions are compared via the resiliency index (see Figure 4), some Florida MSAs and a few California and Arizona regions are labeled as resilient. The maps were then layered to identify better-performing regions in all three aspects (see Figure 5). Only a few regions are relatively stable and resilient while growing fast.⁷

⁶ The darker color is assigned to a high growth, low instability, or high resilience index.

⁷ Three maps were layered by increasing the level of transparency in ArcGIS. A higher transparency unavoidably resulted in lighter colors.

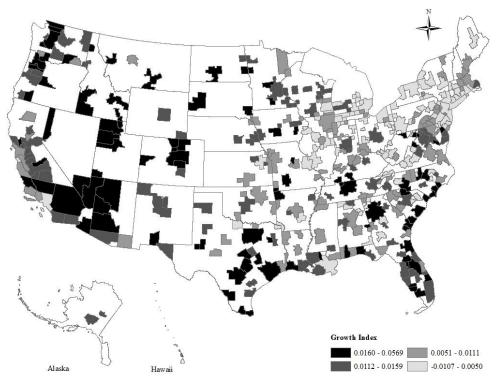


Figure 2. Distribution of Metro Areas based on Growth Index

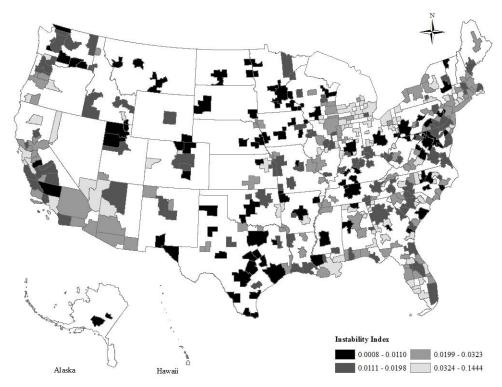


Figure 3. Distribution of Metro Areas based on Instability Index

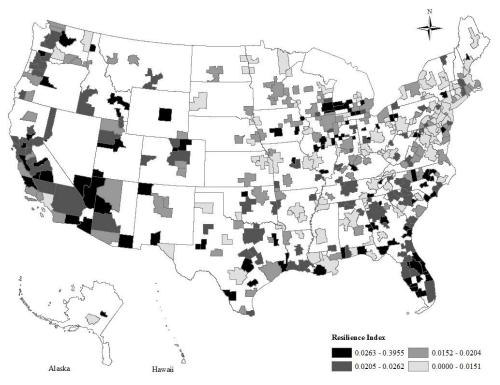


Figure 4. Distribution of Metro Areas based on Resilience Index

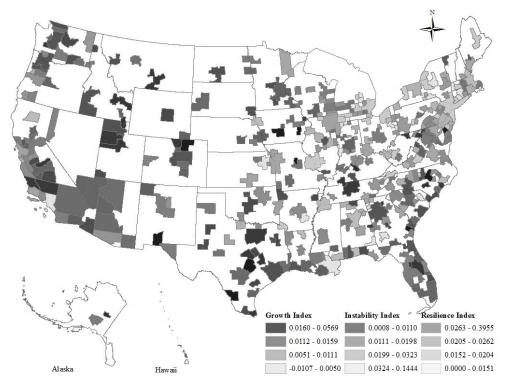


Figure 5. Layered Map of Metro Areas based on All Indices

The results from the analysis show that a good deal of variation exists among MSAs in terms of growth, stability, and resilience. Not surprisingly some spatial autocorrelation appears prevalent in MSA performance on the dimensions of growth, stability, and resilience, when each index is considered separately in turn. Fast-growing regions in the West and the South are located along the line across states in general. Stable regions in the South and the Midwest seem to be in the line, and such an aspect applies to resilient regions in the Western and some part of South. When all three indices are considered simultaneously, however, few are left as growing fast, steadily and resiliently. Some top players are located in better performing parts of the nation such as South near Texas. Others are rather dispersed throughout the nation despite of low performance of their surrounding MSAs.

3. Discussion

In this chapter, I present two new measures of recessionary periods of 382 U.S. metropolitan areas using monthly data from January 1990 through March 2017. The measures have straight forward meaning—the metropolitan economic **instability** is measured as the weighted share of a metropolitan area's employment—based on the last peak prior to any given recession—that was lost *across all of its recessions* and a metropolitan area's recessionary **resilience** is defined as the average employment growth rate *across the recovery* periods of the metropolitan area's recessions. While I use employment as my measure, I could easily have used payroll, although its measurement is complicated by inflation, which can also be locationally specific.

I both codify and gauge the above measures via the metropolitan area's average annual employment growth rate over the study period. Perhaps not so surprisingly, I find both resilient and stable metropolitan economies in the U.S. are apt to grow faster. Curiously, however, stable economies generally are not also very resilient.

I next broke out the metropolitan areas into eight different possible groups by employing the median as a threshold for whether a particular metropolitan area performed well or not on each of the three criteria.⁸ That is, I surmised that it was "good" for a metropolitan area to grow jobs fast, to have stable employment, and to be resilient with respect to employment in the face of recessions. I found that four of the eight categories were heavily loaded, with each containing slightly less than 20% of all U.S. metropolitan areas. Curiously, two were the categories of metropolitan areas that grew fast and were stable; the others were the polar opposite set, which grew slowly and were unstable. This suggests that stable metropolitan areas tend to grow faster but the level of resilience varies greatly among them. Cutting the criteria thresholds at their weighted metropolitan means rather than median values caused some larger metropolitan areas to shift from being classified as stable to unstable. That is, thresholds were not as robust on the instability measure as they were on the other two. This suggests that the instability measure may have a tendency to be highly clustered about its mean value than are the other two measures.

Finally, I examined the geography of the outcomes of the classification scheme. As established elsewhere, from 1990 to 2017 metropolitan areas of the Northeast grew slowly, and those of the West and South were more apt to grow more rapidly. These general growth trends are undoubtedly at least partly connected to general geographic changes in trade

⁸ The third was the metropolitan area's annual average growth rate over the study period.

patterns which moved away from Europe and toward Mexico and the Pacific Rim. Less well known over the study period is that metropolitan areas of the Northeast were also more unstable than most of their equivalents elsewhere in the U.S., and those in the U.S. West tended to be more resilient to their own vagaries. It is exactly this sort of finding that my descriptive, exploratory work was designed to uncover.

CHAPTER 3. CAUSES OF GROWTH, INSTABILITY, AND RESILIENCE

1. Overall Trend

1.1. Data and Methods

This chapter quantitatively examines factors correlated with the growth, instability, and resilience measures of MSAs. The focus of this study is the entire economic system represented simultaneously by the three measures, rather than sole dynamics of each measure. These three measures are connected conceptually as they constitute trajectories of employment in a metropolitan area from various angles and at the same time practically as shown in the correlation table (see Table 2). Therefore, a more precise estimation would come from a regression that reflects the fact that the three measures are correlated to some extent.

Joint-system equations allow for an estimation of a single equation from a larger system of simultaneous equations. The method of joint-system equations is appropriate when the error terms of equations are believed to be correlated and taking account of such a correlation in producing estimates is beneficial. Compared to estimating a single equation one at a time, the inclusion of additional information – a larger system of simultaneous equations – improves efficiency. Two kinds of widely used joint-system equations are seemingly unrelated regressions and three-stage least squares. Seemingly unrelated regressions are used when there is no endogenous regressors in the system of equations, while three-stage least squares are used when there is one or more endogenous regressors in the system.

1.1.1. Seemingly Unrelated Regression

When errors in different equations are correlated, these equations are deemed related. The combination of growth, instability, and resilience equations is believed to be related somehow. Unlike an ordinary least squares regression, seeming unrelated regressions (SUR) use this information when estimating coefficients. A seemingly unrelated regression system, first proposed by Zellner (1962), is a set of linear equations where contemporaneous error terms in these equations are allowed to correlate. Coefficients, standard errors, and R^2 values in this system are different from those in the ordinary least squares regression. The estimates from SUR are believed to be more precise and appropriate for this study, as SUR allows for some level of linkage among the three measures, albeit minimally. SUR uses the asymptotically efficient, feasible, generalized least-squares algorithm described in Greene (2018).

The following three equations constitute the beginning SUR model. This model uses an identical list of right-hand-side variables across equations to allow for the possibility of a variable impacting growth, instability, and resilience all together. The list consists of all variables discussed in Chapter 1, with extra policy and political variables.:

 $Growth = \beta_0 + \beta_1 asset + \beta_2 cst + \beta_3 ltdot + \beta_4 stdot + \beta_5 tir + \beta_6 patent + \beta_7 herf + \beta_8 cons + \beta_9 manu + \beta_{10} gov + \beta_{11} self + \beta_{12} black + \beta_{13} foreign + \beta_{14} coll + \beta_{15} minwage + \beta_{16} emptax + \beta_{17} right + \beta_{18} unemp + \beta_{19} pov + \beta_{20} repub + \beta_{21} span + \varepsilon_1$

Instability = $\beta_0 + \beta_1 asset + \beta_2 cst + \beta_3 ltdot + \beta_4 stdot + \beta_5 tir + \beta_6 patent + \beta_7 herf + \beta_8 cons + \beta_9 manu + \beta_{10} gov + \beta_{11} self + \beta_{12} black + \beta_{13} foreign + \beta_{14} coll + \beta_{15} minwage + \beta_{16} emptax + \beta_{17} right + \beta_{18} unemp + \beta_{19} pov + \beta_{20} repub + \beta_{21} span + \varepsilon_2$

Resilience = $\beta_0 + \beta_1 asset + \beta_2 cst + \beta_3 ltdot + \beta_4 stdot + \beta_5 tir + \beta_6 patent + \beta_7 herf + \beta_8 cons + \beta_9 manu + \beta_{10} gov + \beta_{11} self + \beta_{12} black + \beta_{13} foreign + \beta_{14} coll + \beta_{15} minwage + \beta_{16} emptax + \beta_{17} right + \beta_{18} unemp + \beta_{19} pov + \beta_{20} repub + \beta_{21} span + \varepsilon_3$

where growth is a growth index calculated for the 1990-2017 period; instability is an instability index calculated for the 1990-2017 period; resilience is a resilience index calculated for the 1990-2017 period; asset is total assets per employee in 1990; cst is per capita total cash and securities in 1990; *ltdot* is per capita total long-term debt outstanding in 1990; stdot is per capita short-term debt outstanding in 1990; tir is per capita total intergovernmental revenue in 1990; *patent* is the number of patents per employee in 1990; herf is Herfindahl index calculated by the industrial composition of a metropolitan area in 1990; cons is the percent of construction employees out of employed persons 16 years old and over in 1990; manu is the percent of manufacturing employees out of employed persons 16 years old and over in 1990; gov is the percent of government workers out of employed persons 16 years old and over in 1990; self is the percent of self-employed workers out of employed persons 16 years old and over in 1990; black is the percent of Black persons in 1990; foreign is the percent of foreign born persons including naturalized citizens and non-citizens in 1990; coll is the percent of persons 25 years old and over with some college or higher education in 1990; *minwage* is a state minimum wage on January 1 of 1990); *emptax* is a state average employer tax rate as a percent of total wages in 1990; *right* denotes the existence of right-to-work laws in a state in 1990 (0 if not exist; 1 if exists); *unemp* is an unemployment rate among persons in labor force who are 16 years and over in 1990; pov is the percent of persons whose income is below poverty level in 1990; repub is the percent of votes for the Republican candidate in the 1988 presidential election; and

span is the total number of downturns an MSA has experienced between 1990 and 2017. Table 6 summarizes descriptive statistics of these variables. After missing or unreliable independent variables of some metros are dropped from the original data containing 382 MSAs, the data set for the model is reduced to a total of 279 MSAs.

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
growth	279	0.0108	0.0088	-0.0107	0.0558
instability	279	0.0259	0.0225	0.0008	0.1444
resilience	279	0.0209	0.0104	0.0000	0.0877
asset (\$/employee)	279	49,621.5900	101,974.1000	7.0033	1,064,019.0000
invcapt (\$/employee)*	279	22,532.4700	46,329.1700	-1,434.3400	452,156.9000
cst (\$/person)	279	1,660.2700	1,032.9220	310.9796	7,416.0630
ltdot (\$/person)	279	2,055.1530	3,871.9840	172.6281	61,848.4600
stdot (\$/person)	279	43.9978	73.4713	0.0000	501.2372
tir (\$/person)	279	724.9470	248.3513	138.2970	1,949.2260
herf (point)	279	0.0968	0.0149	0.0790	0.2210
patent (count/employee)	279	0.0004	0.0004	0.0000	0.0041
cons (%)	279	6.3260	1.5733	3.6129	12.4428
manu (%)	279	18.3157	7.9654	3.7036	48.3538
gov (%)	279	15.7898	5.6238	6.6350	38.2238
self (%)	279	6.9560	1.7045	4.1893	13.0531
black (%)	279	9.5342	9.8399	0.0667	42.9655
foreign (%)	279	4.3270	4.8164	0.3888	30.7811
coll (%)	279	45.0907	8.8475	24.8081	71.2220
minwage (\$)	279	3.0235	1.4041	0.0000	4.3000
emptax (%)	279	0.7629	0.3449	0.2500	2.6900
right (N/A)	279	0.4086	0.4925	0.0000	1.0000
unemp (%)	279	5.9733	1.6694	2.7060	14.3089
pov (%)	279	12.9542	4.6764	5.8545	41.8768
repub (%)	279	55.8457	8.9372	31.2322	80.3260
span (count)	279	7.1505	3.0403	1.0000	18.0000

Table 6. Descriptive Statistics of Variables to be Included in the Model

Notes.

All dollars are nominal.

* invcapt denotes total invested capital per employee. This variable is not included in this seemingly unrelated regression but becomes part of the following model, a three-stage least squares regression.

The measured growth, instability, and resilience for the period of 1990 to 2017, called as "the pooled period" hereafter, serve as dependent variables. Each MSA has a nonmissing value for the three measures, except for four that could not recover its highest employment level occurred after the start of the study period until the end of the study period. In such cases, the resilience measure does not produce a valid number, resulting in a missing value. These missing values are replaced by zero for regressions to prevent the loss of observations.

The three equations have the identical list of independent variables. The identical list is adopted assuming that a factor affecting one of the three measures might also have an impact on the other measures. There exists a long history of growth research, identifying several reliable factors. Studies on fluctuations also have a pool of meaningful factors, although the concept of instability – lost employment – has not been incorporated in those studies. On the other hand, attempts to identify resilience-related factors are still developing. Considering the relatedness of the three measures, it is reasonable to apply identified factors from growth and fluctuation studies to the resilience equation.

A set of independent variables begins with what theory and empirical research have suggested and expands further by the inclusion of additional political information. All of the above independent variables are collected for 1990, the starting year of the analytic period. Due to the frequent change in boundaries of MSAs over time,⁹ independent variables are collected at the county level and reconstructed to metropolitan level data based on the most recent delineations of Metropolitan Statistical Areas, published by the Office of Management and Budget (OMB) on July 15, 2015. In sum, each independent variable represents an MSA's status in 1990 and each dependent variable indicates an MSA's employment path between 1990 and 2017.

⁹ During the period of study, county boundaries remain fixed over time.

Major factors suggested in theory but not appeared in existing research are savings and investment of the private sector. More specifically, savings rates (Solow, 1956; Swan, 1956), the amount of total investments (Phelps, 1962; King & Rebelo, 1986; Stadler, 1990; Jones et al., 2000), and the level of financial constraints (Aghion et al., 2010) are thought to be related to stability and resilience. Since public data are unavailable for the suggested explanatory variables of savings rates and investment of individuals, this study uses companies', state, and local government financial information as a proxy. First, the *Compustat* available through the Wharton Research Data Services contains yearly financial information of global companies, which covers 99 percent of the market capitalization. It includes information on total assets and total invested capital for most companies in the United States. Total invested capital is a sum of total common equity, total long-term debt, minority interest, and total preferred stock. These two variables are composed at the MSA level and divided by total employees in MSA, and these per employee figures are used in the regression models as a proxy for financial constraints. Both assets and invested capital are expected to be negatively correlated with instability and positively correlated with growth and resilience. In addition to their relationship with the three indices, another matter of attention is whether or not these variables are critical in this empirical test as much as they are in theories.

Given that private-sector finance is related to stability and resilience, it is plausible to assume that the public-sector finance may also have a relationship. U.S. public finance is administered at the federal, state, local levels exclusively. Metropolitan statistical areas are not a unit that operates its own fiscal system. The next largest geographical entity next to a metropolitan area is the county and thus financial information at the county or smaller

geographical entities are collected and restructured by the author as metropolitan-level variables. Local governmental finance information comes from the Annual Surveys of State and Local Government Finances available through the U.S. Census Bureau.¹⁰ It reports statistics for county, municipality, township, special district, and school district. As statistics for each of these governments are mutually exclusive, each variable is summed by county and then composed at the MSA level for analyses. Then these statistics are divided by total population in all counties with valid statistics per MSA to produce per capita figures. Final variables used in the regression models are per capita total long-term outstanding debt, per capita short-term outstanding debt, per capita total cash and securities, and per capita total intergovernmental revenue. All dollars are nominal. The debt is likely to reflect governments' adverse financial condition but may reflects the active participation of governments in the economy. The relationship of debt to the three indices would be negative if it is the prior case, but can be positive if it is the latter case. Cash and securities and intergovernmental revenue are expected to decrease instability and increase resilience in crises. In particular, intergovernmental revenue is used as a proxy for network which is indeed mentioned as a positively influencing factor in empirical studies.

Next, quality-improving innovation is realized in the model through the number of patents issued annually in each metropolitan area. County level patent counts are collected from the United States Patent and Trademark Office¹¹ and reconstructed to metropolitan level data by the author.

¹⁰ Retrieved on May 19, 2018 from https://www2.census.gov/pub/outgoing/govs/special60 (link requested via email)

¹¹ Retrieved on March 8, 2017 from https://www.uspto.gov/web/offices/ac/ido/oeip/taf/reports_cbsa.htm

Theory also suggests the variety of product and diversification of activities is related to cyclicity. This study uses a widely used measure for economic diversity, the Herfindahl index, to represent the product diversity. The level of diversification of economic activities along with economic structure is the most frequently stated explanatory factor in empirical research (Conroy, 1975; Brown & Pheasant, 1985; Malizia & Ke, 1993; Siegel et al., 1995; Acemoglu & Zilibotti, 1997; Wagner & Deller, 1998; Chandra, 2002). Both Decennial Censuses and American Community Survey provide employee counts by industry. The *1990 Decennial Census* is retrieved from the National Historical Geographic Information System and used for the pooled period and the first analytic period starting 1990.¹² In addition to the Herfindahl index, these data are used to create percentages of construction, manufacturing, government, and self-employed persons within a metropolitan area, which are included in the models as independent variables apart from the Herfindahl index itself.

Empirical research also identified several demographic characteristics have explanatory power. Percent of black residents, percent of foreign-born residents, and percent of residents 25 years and over with some college or higher education are excerpted from the *1990 Decennial Census* to be included in the model.

In addition to these variables discussed in the existing literature, a set of state policies relevant to employment are added to the models to see whether or not these policies directly intended to improve the labor market may positively contribute to the growth, stability, and resilience in the labor market. State minimum wage,¹³ average employer tax

¹² Retrieved on August 27, 2015 from https://nhgis.org

¹³ Retrieved on March 20, 2017 from http://knowledgecenter.csg.org/kc/content/book-states-archive-1935-2009

rate as a percent of total wages in a state,¹⁴ existence of right-to-work law in a state¹⁵ are included in the models. Although not prominently appearing in business cycle literature, minimum wage and earned income tax credit are among the factors that affect demand of employment (Ehrenberg & Smith, 2016). The state average employer tax rate is state unemployment taxes paid by employers divided by total wages paid in covered employment. Unemployed persons may receive unemployment insurance benefits from a state in which they live. If a state faces high unemployment and does not have enough funds to pay all benefits, it borrows money from the federal government. To manage the payment of unemployment benefits this way, both state and federal governments collect unemployment taxes from employers. While the federal unemployment tax rate is identical throughout the nation,¹⁶ the state unemployment tax rates vary widely across states as every state sets its own tax rates. Therefore, the average state employer tax rate may indicate how actively a state protects the safety net for unemployed workers.

To capture the economic condition that a metropolitan area faces at the start of each period, unemployment rate among persons in labor force who are 16 years old and over and percent of residents who are in poverty are calculated using the *1990 Decennial Census*. The level of political stance of residents is represented by percent of votes for Republican candidate. The *Dave Leip's Atlas of US Presidential Elections* data available through Data-Planet[™] Statistical Datasets by Conquest Systems, Inc.¹⁷ contains county-level vote counts

¹⁴ Retrieved on March 20, 2017 from https://workforcesecurity.doleta.gov/unemploy/chartbook.asp

¹⁵ Retrieved on March 20, 2017 from https://en.wikipedia.org/wiki/Right-to-

 $work_law \# U.S._states_with_right-to-work_laws$

¹⁶ When a state cannot pay back the loan borrowed from the federal government to cover unemployment benefits within two years, the real federal unemployment tax rate imposed on employers in the state becomes higher than the rest of the nation.

¹⁷ Retrieved on November 2, 2017 from http://statisticaldatasets.data-planet.com

by party at the U.S. Presidential elections. The 1988 Presidential election data are used to create percent of votes for Republican candidate for 1990. The number of downturns that a metropolitan area experiences over each study period is included to see if there is a correlation between any of the three measurements and the frequency of downturns. Lastly, growth, instability, and resilience measures are included in the models as control variables.

Several variables were included in preliminary models but later dropped from the model due to their statistical insignificance and/or critically negative impact on the fit of the model. Such variables are (1) percent of Hispanic residents, (2) percent of households at various household income levels, (3) percent of owner-occupied housing units at various housing values, and (4) state Earned Income Tax Credit rate as a percent of federal EITC.¹⁸ The inclusion of total employee count, used with purpose of capturing the size or agglomeration effect of MSAs on the three measures, resulted in a high collinearity with the number of patents and thus was excluded from the final model. In relation to the publicsector finance, state governmental finance information, exclusive of local revenues or spending, was derived from the Annual Surveys of State and Local Government Financesas available through the Tax Policy Center at the Urban Institute and Brookings Institution¹⁹—and was included in preliminary models. Among revenue, expenditure, debt, and assets for state governments, per capita total long-term debt outstanding, per capita total short-term debt outstanding, per capita cash and securities, per capita intergovernmental revenue, per capita employee retirement expenditure, and per capita unemployment compensation expenditure were selected. These variables, however,

¹⁸ Retrieved on March 20, 2017 from http://users.nber.org/~taxsim/state-eitc.html

¹⁹ Retrieved on May 14, 2018 from http://slfdqs.taxpolicycenter.org/pages.cfm

showed high collinearity with county and lower-level finance statistics and, therefore, were excluded them in the final model.

1.1.2. Three-Stage Least Squares

The degree to which the three measures are related is further increased in a threestage least squares (3SLS) first proposed by Zellner and Theil (1962). The 3SLS system estimates a set of linear equations simultaneously. A dependent variable has its usual interpretation as the left-hand-side variable in an equation with an associated disturbance term. However, all dependent variables are explicitly taken to be endogenous to the system and are treated as correlated with the disturbances in the system's equations, meaning that they are adjusted through the interactions within the system rather than given exogenously by the raw data. The 3SLS system constructed for this study contains three equations – growth, instability, and resilience – and estimate their coefficients simultaneously. Three dependent variables remain unchanged – growth, instability, and resilience measures – as they were in the previous SUR model. But unlike with the SUR model, each dependent is included in the other two equations and, hence, is now treated as "endogenous" independent variables in the other two equations.

This study's 3SLS system treats all other right-hand-side variables as exogenous to the system and uncorrelated with the disturbances, as they were in the SUR model. Such exogenous variables act as instruments for the endogenous variables in the system, defining each equation and thus differentiating one equation from another. Both this feature and the endogenous nature of the three measures in the system require each equation to include at least some unique right-hand-side variables. The almost identical list of explanatory variables used for the SUR model is therefore modified in a way that a variable believed to be correlated exclusively with one of the three measures is now included in the corresponding equation only. For example, while a variable thought of as being related to growth was included in all three equations in the SUR model, it is now part of the growth equation only.

The following three equations constitute the 3SLS model and right-hand-side variables unique to each equation are boldfaced for easier identification:

 $Growth = \beta_0 + \beta_1 invcapt + \beta_2 ltdot + \beta_3 patent + \beta_4 cons + \beta_5 manu + \beta_6 black + \beta_7 foreign + \beta_8 coll + \beta_9 minwage + \beta_{10} emptax + \beta_{11} right + \beta_{12} unemp + \beta_{13} pov + \beta_{14} repub + \beta_{15} instability + \beta_{16} resilience + \varepsilon_1$

Instability = $\beta_0 + \beta_1 asset + \beta_2 cst + \beta_3 herf + \beta_4 gov + \beta_5 black + \beta_6 foreign + \beta_7 coll + \beta_8 minwage + \beta_9 emptax + \beta_{10} right + \beta_{11} unemp + \beta_{12} pov + \beta_{13} repub + \beta_{14} span + \beta_{15} growth + \beta_{16} resilience + \varepsilon_2$

Resilience = $\beta_0 + \beta_1 \operatorname{stdot} + \beta_2 \operatorname{tir} + \beta_3 \operatorname{self} + \beta_4 \operatorname{black} + \beta_5 \operatorname{foreign} + \beta_6 \operatorname{coll} + \beta_7 \operatorname{minwage} + \beta_8 \operatorname{emptax} + \beta_9 \operatorname{right} + \beta_{10} \operatorname{unemp} + \beta_{11} \operatorname{pov} + \beta_{12} \operatorname{repub} + \beta_{13} \operatorname{span} + \beta_{14} \operatorname{growth} + \beta_{15} \operatorname{instability} + \varepsilon_3$

where *growth* is a growth index calculated for the 1990-2017 period; *instability* is an instability index calculated for the 1990-2017 period; *resilience* is a resilience index calculated for the 1990-2017 period; *asset* is total assets per employee in 1990; *invcapt* is total invested capital per employee in 1990; *cst* is per capita total cash and securities in 1990; *ltdot* is per capita total long-term debt outstanding in 1990; *stdot* is per capita short-term debt outstanding in 1990; *tir* is per capita total intergovernmental revenue in 1990; *patent* is the number of patents per employee in 1990; *herf* is Herfindahl index calculated

by the industrial composition of a metropolitan area in 1990; cons is the percent of construction employees out of employed persons 16 years old and over in 1990; manu is the percent of manufacturing employees out of employed persons 16 years old and over in 1990; gov is the percent of government workers out of employed persons 16 years old and over in 1990; self is the percent of self-employed workers out of employed persons 16 years old and over in 1990; black is the percent of Black persons in 1990; foreign is the percent of foreign born persons including naturalized citizens and non-citizens in 1990; coll is the percent of persons 25 years old and over with some college or higher education in 1990; *minwage* is a state minimum wage on January 1 of 1990); *emptax* is a state average employer tax rate as a percent of total wages in 1990; right denotes the existence of rightto-work laws in a state in 1990 (0 if not exist; 1 if exists); unemp is an unemployment rate among persons in labor force who are 16 years and over in 1990; pov is the percent of persons whose income is below poverty level in 1990; repub is the percent of votes for the Republican candidate in the 1988 presidential election; and span is the total number of downturns an MSA has experienced between 1990 and 2017.

The R^2 reported is the most convenient parameter to be used to check the fit of a model in general, as it explains the percent of variance explained by the predictors. This is not the case for 3SLS. The usefulness of R^2 is smaller in 3SLS than in ordinary least squares. R^2 is equal to 1 – RSS/TSS, where RSS denotes the sum of squared residuals "sum of (y – Xb)²" and TSS denotes the total sum of squared deviations from the mean of the dependent variable "sum of (y – ybar)²." In ordinary least squares, RSS and TSS are calculated based on the same projection line, constraining RSS to be smaller than TSS. As a result, R^2 ranges from 0 to 1. In an instrumental variables model, such as 3SLS, some independent variables

(e.g., *invcapt*) are used as instruments for endogenous independent variables (e.g., *growth*) when the model is estimated. This line minimizes the sum of squared residuals with the instrumentalized variables being used. But R^2 remains calculated based on the actual values, not the instrumented values, of the endogenous independent variables. Thus, the actual values are not on the projection line and, hence, RSS estimated from the actual values is no longer constrained to be less than TSS. If RSS is greater than TSS, R^2 becomes negative and is, therefore, not a good indicator of a model's fit in 3SLS.

A firm theoretical basis and reasonable standard errors are alternative criteria for determining the fit of a 3SLS model. The system of equations in this study extensively include variables appearing in theories and empirical research, as long as data are available and not collinear. The three equations are structurally linked to reflect their believed correlation. Reported standard errors are acceptable as shown in the following result section. Thus, I regard the model proposed for this study satisfies these criteria.

Another criterion to assure the proposed model is well structured is the identifiability of the model. A model is identifiable if there are knowns as enough as unknowns and there is one best value for each parameter. A model is not identifiable or un(der)identified if it there are fewer knowns than unknowns and each parameter may take an infinite number of values. A lack of identification can occur in simultaneous models where identical variables appear in different equations. The achievement of identifiability requires two conditions. First, the number of endogenous variables in the system of equations minus 1 must be less than the number of exogenous variables excluded from the equation but included in the remaining equations of the system. This is called the order condition, which is necessary for identification. Second, any equation must not depend

linearly on another equation in the system. Based on the matrix of coefficients of all equations in the system, a matrix must be constructed for an equation from the remaining equations; contain rows and columns of the number of all equations minus 1; and have a nonzero determinant. This is called the rank condition, also a necessary and sufficient condition for identification. Detailed are found in Fisher (1966), Gujarati (2009), Theil (1971), and Greene (2018). The model proposed for this study meets both the order and rank conditions.

In addition, I set my own criterion on R^2 . A negative R^2 does not indicate that a model is incorrectly specified, but implies that the simple means of the dependent variables provide a better fit to the outcomes than do the fitted values. In other words, the model predicts the dependent variable worse than the mean model. I have concluded that parameter estimates from such a model are "actually" not useful and modeling has not been finalized until a positive R^2 is reported. The current model reports a positive R^2 , as shown in the following section.

The model is set to iterate for more accurate estimates. Both iterated and noniterated parameter estimates are reported in the result section to detect a difference if any.

1.2. Results

1.2.1. Seemingly Unrelated Regression

The growth equation has a higher number of statistically significant variables than do the instability and resilience equations, and the degree of significance among the statistically significant variables of the instability equation tends to be greater than that of the resilience equation (see Table 7). This finding implies that quantifiable factors explain the long-term tendency better than they do short-run fluctuations and that resilience in particular may relate more closely to quantitative aspects.

Still, this SUR structure shows several variables were worth considering. The first group of such variables is that which shows a consistent positive or negative correlation with the overall employment dynamics without any conflicting impact. More long-term debt by local governments, a higher share of construction employees, and a higher share of college or higher education among residents induce growth and resilience, without negatively affecting stability. The long-term debt (recall this is at the start of the study period) may indicate that local governments have a far-sighted plan for their economy, an active involvement, or a combination of the two, leading to a positive influence on the regional economy. Vibrant construction activities at the start of the study period (and separate from long-term debt) may indicate a prosperous economic starting condition—such a good condition is apt to sustain subsequent short- and long-run growth rates. This finding in part supports the path-dependency literature. Higher educational attainment has appeared in literature as a positive regressor fairly consistently, and it acts again so in this model.

A higher state employer tax rate, a higher poverty rate, a lower percent of Black residents, and a lower unemployment rate contribute to growth and stability. A more active involvement of a state government in creating a secure safety net for the unemployed, represented by a higher state unemployment tax rate imposed on employers, leads to a stable labor market as well as a long-run increase in regional employment. A higher poverty rate may be an indicator of a higher growth potential in a metropolitan area and those who are in poverty may be willing to work in any adverse economic situation, counteracting the regional employment loss. Black residents may take a great portion of low-skilled manufacturing industries that were based in the United States in the past but are now related overseas, and therefore the higher proportion of Black residents may show a negative relationship with growth and stability. A lower unemployment rate is related to a more stable economy, which indicates that a healthy labor market helps a metropolitan area stay still against fluctuations, and also contributes to a faster long-term growth.

One variable that relates to the short-term downward and upward movements is how often a metropolitan area has experienced over the study period. The more frequent experience helps the metropolitan area prevent itself from losing employment and helps it regain lost employment quickly. What a mero area has learned from previous downturns is however unknown in this regression and needs future, mostly qualitative, research.

Unlike these consistent variables, three variables show inconsistent relationships across equations. A metropolitan area with a more diverse industrial structure loses more employment in the face of a downturn but experiences a faster recovery. A higher minimum wage leads to the opposite outcome. It appears to help a metropolitan area reduce its employment losses but its inflexibility could be an obstacle for the area to regain its lost employment. A higher share of manufacturing employees negatively relates to the longterm upward movement, growth, but is positively related to the short-term upward movement, resilience.

This SUR model reveals a few variables to consider if a metropolitan area attempts to improve its economic path, but some variables reveal a complex relationship with the dependent variables, reducing a potential to be a policy tool. It may be because the minimal level of correlation assumed for the three equation (i.e., correlation in error terms) does not reflect the actual deeper relationship. It is now time to see if the 3SLS model results in improved parameters or the findings from the SUR model are at least supported by the 3SLS model.

	Grow	vth	Instability		Resilience	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
asset	-3.03E-09	3.89E-09	-1.20E-08	1.07E-08	-1.10E-08*	6.62E-09
cst	1.16E-07	4.72E-07	-1.29E-06	1.30E-06	-1.04E-06†	8.05E-07
ltdot	1.87E-07†	1.27E-07	4.73E-08	3.50E-07	2.90E-07†	2.16E-07
stdot	-1.29E-06	6.06E-06	-2E-05	1.67E-05	-1.4E-05†	1.03E-05
tir	1.91E-06	1.69E-06	2.31E-06	4.66E-06	-1.01E-07	2.88E-06
patent	-0.6186	0.9987	-1.1891	2.7511	-1.6935	1.7019
herf	-0.0320	0.0315	0.7627***	0.0866	0.1069**	0.0536
cons	0.0016***	0.0003	-0.0010	0.0008	0.0007†	0.0005
manu	-0.0002**	8.23E-05	-5.8E-05	0.0002	0.0002*	0.0001
gov	-0.0004***	9.37E-05	-6.4E-05	0.0003	-0.0002	0.0002
self	0.0001	0.0003	0.0016**	0.0008	0.0004	0.0005
black	-0.0002***	5.08E-05	0.0006***	0.0001	-4.76E-07	8.66E-05
foreign	-9.5E-05	9.06E-05	0.0004†	0.0002	8.15E-05	0.0002
coll	0.0004***	6.51E-05	-0.0002	0.0002	0.0004***	0.0001
minwage	0.0004	0.0004	-0.0015†	0.0010	-0.0009†	0.0006
emptax	0.0032***	0.0012	-0.0061*	0.0034	-0.0005	0.0021
right	0.0033***	0.0010	-0.0016	0.0028	0.0006	0.0017
unemp	-0.0019***	0.0004	0.0063***	0.0010	0.0004	0.0006
ppov	0.0010***	0.0002	-0.0025***	0.0004	-9.7E-05	0.0003
repub	0.0002***	4.68E-05	-9.9E-05	0.0001	3.38E-05	7.97E-05
span	-1.7E-05	0.0001	-0.0024***	0.0004	0.0004*	0.0002
_cons	-0.0225***	0.0065	-0.0182	0.0180	-0.0154†	0.0111
n	279		279		279	
R^2	0.59	23	0.5313		0.1640	

Table 7 Comminal	Unveloted Decreasion	Estimotes.	1000 2017
Table 7. Seemingly	Unrelated Regression	Estimates.	1990-201/

Notes.

The coefficients and standard errors are rounded up to four significant figures.

*, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test.

† indicates statistical significance at the 90% level under the one-tailed test.

1.2.2. Three-Stage Least Squares

The three equations of the 3SLS model have several right-hand-side variables in common. Among the shared variables, the growth equation contains more significant variables than the instability and resilience equations (see Table 8). The degree of

significance (i.e., p value) is also higher in the growth equation than the instability or resilience equation. R^2 for the resilience equation is notably lower than those for the other two. This difference implies that quantifiable factors appearing in economic dynamics literature have a smaller explanatory power on resilience than on growth or instability. Given that this model contains not only those discussed in the literature but a broad range of socioeconomic factors that one may imagine with respect to employment, it is reasonable to assume that non-quantifiable processes that occur within each metropolitan area may be critical in determining the metropolitan resilience. A complete set of factors related to resilience would be achievable if additional unknown quantifiable or nonquantifiable factors are discovered.

The 3SLS and the SUR share several statistically significant variables but the 3SLS structure has two advantages. The 3SLS structure allows for a higher level of correlation among the three equations than does the SUR structure, when estimating coefficients. This structure should better reflect the real-world relationships. Furthermore, in case a variable shows significance in more than two equations, its parameter signs never conflict with a rule to be a potential policy tool. If the variable is positively related to growth, then it is negatively related to instability or positively related to resilience, and vice versa. The concern raised after review of the SUR outcome is resolved in the 3SLS model and, hence, this model appears to fit the employment dynamics better.

A lower unemployment rate is related to a faster growth, a more stable economy, and higher resiliency. A higher poverty rate, a higher state average employer tax rate, and a lower percent of Black residents are associated with a faster long-term growth and a less employment loss in the face of a downturn. A higher percent of college or higher education induces both growth and resilience, while not affecting stability. These variables were statistically significant in the previous SUR model too. Their significance in both models confirms their importance in explaining the labor market dynamics in recent decades. This then implies that they may be considered as effective policy tools for strengthening metropolitan labor markets.

An interesting finding is on the number of downturns that a metropolitan area has experienced over the study period. The more downturns experienced, the more stable and more resilient the economy. Recalling that this study calculates downturns not by the national recessions but by each metropolitan area's employment losses over time, so called regional and local downturns, this finding implies that metropolitan areas are indeed vaccinated by each downturn. The behind the scene processes are unknown at this moment, but it could be their financial, operational, or administrative preparations for maintaining a stable labor market.

In addition to those that have a relationship with two or more indices, several variables show a relationship with the indices albeit one at a time. A faster growth in a metropolitan area is induced by an increase in the following variables: the per capita long-term debt of local governments within a metropolitan area, the percent of construction employees, the state minimum wage, and the percent of votes for the Republican candidate in the preceding presidential election. The existence of right-to-work laws in a state and a decrease in the percent of manufacturing employees are also related to the faster growth. A more diverse industrial structure represented by a higher Herfindahl index is related to a greater employment loss in the face of a downturn, while a higher total per employee asset of firms and a higher percent of government employees in a metropolitan area help reduce

the loss. Once a downturn occurs, a higher percent of self-employed persons and a lower per capita short-term debt of local governments help a metropolitan area recover quickly.

The way the resilience index is structured already reflects the depth of a downturn and the length of a recovery period, but the mutual relationship between the instability and resilience indices drawn from this model still shows that the more the employment is lost during a downturn, the faster the recovery from a trough to a pre-downturn employment level. This finding must be cautiously interpreted. This result does not imply that a metropolitan area must lose a great deal of employment to be resilient. Rather, it should be interpreted that a smaller loss of employment during a downturn does not guarantee a quick return to the pre-downturn status. Other variables including those that are stated in the preceding paragraphs are expected to expedite or delay recovery.

The growth equation reveals that growth in this model structure is not influenced by the instability and resilience measures. This result implies that the 3SLS structure has extracted short-term changes (i.e., instability and resilience) from long-term movement (growth). The instability and resilience equations reveal a great deal of influence on each other, which conveys an unavoidable interconnection between the short-run downward move and the short-run upward move. Considering that these measures act as a control variable in each equation, however, other statistically significant regressors are free from the influence of instability or resilience measure.

To gauge the degree of influence among statistically significant variables, standardized coefficients are reported in the columned named as Beta. For the growth equation, the poverty rate has the greatest influence, followed by the percent of Black residents, the percent of college or higher education, the percent of construction employees, the unemployment rate, the percent of votes for a Republican presidential candidate, and the existence of right-to-work laws in a state. The instability equation is determined largely by the frequency of experiencing downturns in the given period, followed by the unemployment rate, the Herfindahl index, and the poverty rate. The frequency of experiencing a downturn in the given period is the most influential determinant of the resilience equation, and the unemployment rate the percent of college or higher education follow.

		Growth			Instability			Resilience	
	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta
invcapt	3.96E-09	8.88E-09	0.0209						
ltdot	1.96E-07**	8.53E-08	0.0865						
patent	-0.8399	0.9671	-0.0413						
cons	0.0014***	0.0003	0.2538						
manu	-0.0002*	0.0001	-0.1482						
asset				-1.38E-08†	8.96E-09	-0.0625			
cst				-7.46E-07	7.87E-07	-0.0342			
herf				0.4900***	0.1010	0.3249			
gov				-0.0004**	0.0002	-0.1015			
stdot							-9.06E-06†	6.38E-06	-0.0638
tir							1.05E-06	1.87E-06	0.0249
self							0.0006†	0.0003	0.0903
black	-0.0002***	4.75E-05	-0.2679	0.0004**	0.0002	0.1662	-2.95E-05	0.0001	-0.0278
foreign	-1.49E-05	0.0001	-0.0082	0.0002	0.0002	0.0500	-2.75E-05	0.0001	-0.0127
coll	0.0003***	0.0001	0.2659	-0.0002	0.0002	-0.0645	0.0002*	0.0001	0.1286
minwage	0.0005†	0.0004	0.0835	-0.0005	0.0010	-0.0291	-0.0004	0.0006	-0.0594
emptax	0.0029**	0.0012	0.1137	-0.0045†	0.0032	-0.0692	0.0007	0.0019	0.0236
right	0.0036***	0.0010	0.2019	-0.0021	0.0029	-0.0462	0.0008	0.0017	0.0375
unemp	-0.0013***	0.0004	-0.2449	0.0048***	0.0011	0.3547	-0.0009†	0.0006	-0.1365
pov	0.0007***	0.0001	0.3834	-0.0015***	0.0005	-0.3076	0.0001	0.0002	0.0598
repub	0.0002***	4.87E-05	0.2093	-0.0001	0.0001	-0.0570	0.0001	0.0001	0.0490
span				-0.0027***	0.0004	-0.3577	0.0009***	0.0002	0.2554
growth				-0.3315	0.3590	-0.1290	0.2380	0.2047	0.2000
instability	-0.0157	0.0337	-0.0403				0.2575***	0.0584	0.5558
resilience	0.1134	0.1528	0.1349	1.1288***	0.4203	0.5229			
_cons	-0.0251***	0.0057	-1.55E-08	-0.0071	0.0142	2.76E-08	-0.0046	0.0083	-2.52E-08
n		279			279			279	
R^2		0.5858			0.5703			0.3049	

Table 8. Iterated Three-Stage Least Squares Estimates, 1990-2017

Notes. The coefficients and standard errors are rounded up to four significant figures.

*, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test. † denotes statistical significance at the 90% level under the one-tailed test.

An iterated 3SLS theoretically produces the most reliable parameter estimates but not all models are guaranteed to converge to a stable point. This pooled period model has reached a convergence but the iteration in categorical models that follow in the coming sections has not been successful. To conjecture the loss of information attributable to the unsuccessful iteration, how much iterated parameter estimates differ from non-iterated estimates is examined based on the pooled period model outputs. As shown in Table 9, significant variables are similar between the two settings. The iteration lowers p values of each parameter estimate, resulting in an increase in the total number of statistically significant explanatory variables. Four variables that show statistical significance in the iterated setting only are total assets per employee in the instability equation, per capita short-term debt, the percent of self-employed workers, and the unemployment rate in the resilience equation. All of these four variables show statistical significance in the one-tailed test, indicating that they are marginal rather than strong regressors. All other significant explanatory variables have the same directions and similar magnitudes in both settings. Rsquared also remains almost unchanged. The iterated setting shows 0.59, 0.57, and 0.30 in the growth, instability, and resilience equations while the non-iterated has 0.59, 0.59, and 0.32 respectively. The categorical models in the coming sections may thus be regarded as acceptable, albeit not iterated.

Table 9. Iterated and Non-iterated Three-Stage Least Squares Estimates, 1990-2017

	Itera	ted	Non-iterated			
	Coef.	Std. Err.	Coef.	Std. Err.		
Growth						
invcapt	3.96E-09	8.88E-09	3.65E-09	8.81E-09		
ltdot	1.96E-07**	8.53E-08	1.89E-07**	8.45E-08		
patent	-0.8399	0.9671	-0.8227	0.9661		
cons	0.0014***	0.0003	0.0014***	0.0003		
manu	-0.0002*	0.0001	-0.0002*	0.0001		

	Itera	ted	Non-ite	erated
	Coef.	Std. Err.	Coef.	Std. Err.
black	-0.0002***	4.75E-05	-0.0002***	4.67E-05
foreign	-1.49E-05	0.0001	-1.44E-05	0.0001
coll	0.0003***	0.0001	0.0003***	0.0001
ninwage	0.0005†	0.0004	0.0005†	0.0004
emptax	0.0029**	0.0012	0.0029**	0.0012
right	0.0036***	0.0010	0.0036***	0.0010
unemp	-0.0013***	0.0004	-0.0013***	0.0004
pov	0.0007***	0.0001	0.0007***	0.0001
repub	0.0002***	4.87E-05	0.0002***	4.79E-05
instability	-0.0157	0.0337	-0.0175	0.0332
resilience	0.1134	0.1528	0.1208	0.1510
_cons	-0.0251***	0.0057	-0.0253***	0.0056
Instability				
asset	-1.38E-08†	8.96E-09	-1.38E-08	1.08E-08
cst	-7.46E-07	7.87E-07	-9.20E-07	9.73E-07
herf	0.4900***	0.1010	0.5593***	0.1086
gov	-0.0004**	0.0002	-0.0004**	0.0002
black	0.0004**	0.0002	0.0004***	0.0001
foreign	0.0002	0.0002	0.0003	0.0002
coll	-0.0002	0.0002	-0.0001	0.0002
minwage	-0.0005	0.0010	-0.0007	0.0010
emptax	-0.0045†	0.0032	-0.0049†	0.0031
right	-0.0021	0.0029	-0.0022	0.0028
unemp	0.0048***	0.0011	0.0051***	0.0011
pov	-0.0015***	0.0005	-0.0016***	0.0005
repub	-0.0013	0.0001	-0.0002	0.0001
span	-0.0027***	0.0004	-0.0025***	0.0004
growth	-0.3315	0.3590	-0.1762	0.3731
resilience	1.1288***	0.4203	0.7981†	0.4918
	-0.0071	0.0142	-0.0089	0.0138
_cons Resilience	-0.0071	0.0142	-0.0089	0.0158
	0.04E.04+	6.38E-06	8 60E 06	7.760.06
stdot	-9.06E-06†		-8.60E-06	7.76E-06
tir	1.05E-06	1.87E-06	1.03E-07	2.37E-06
self	0.0006†	0.0003	0.0003	0.0004
black	-2.95E-05	0.0001	-2.52E-05	0.0001
foreign	-2.75E-05	0.0001	-2.34E-05	0.0001
coll	0.0002*	0.0001	0.0001†	0.0001
minwage	-0.0004	0.0006	-0.0004	0.0005
emptax	0.0007	0.0019	0.0005	0.0018
right	0.0008	0.0017	0.0005	0.0017
unemp	-0.0009†	0.0006	-0.0007	0.0006
pov	0.0001	0.0002	0.0001	0.0002
repub	0.0001	0.0001	3.81E-05	0.0001
span	0.0009***	0.0002	0.0009***	0.0002
growth	0.2380	0.2047	0.3178†	0.2072
instability	0.2575***	0.0584	0.2557***	0.0577
_cons	-0.0046	0.0083	-0.0015	0.0085

	Iterate	ed	Non-iterated			
	Coef.	Std. Err.	Coef.	Std. Err.		
n	27	9		279		
R^2 (Growth)	0.585	8	0.5878			
R^2 (Instability)	0.570	3	0.5	5926		
R^2 (Resilience)	0.304	9	0.3245			

Notes.

The coefficients and standard errors are rounded up to four significant figures.

*, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test.

† indicates statistical significance at the 90% level under the one tailed test.

2. Trend by National Recessions

2.1. Data and Methods

Heterogeneity must exist among metropolitan areas and categorical analyses may rule out this heteroskedasticity. The following sub sections may be regarded as sensitivity tests of the reported parameter estimates from the pooled period model. Among the two models used to figure out the general trends – SUR and 3SLS – 3SLS is conceptually more suitable than SUR as it allows for the intertwined and hence more realistic relationship among the three equations. In addition, the estimated parameters from the 3SLS model reflect statistically significant variables in a more conservative way, by converting marginally significant variables in SUR to completely insignificant ones in 3SLS. Herfindahl index shows a direction opposed to the supposition, but as it is the only parameter showing abnormality in 3SLS and its direction shown in SUR does not reflect the expected direction either. I have concluded that 3SLS is more appropriate for analyzing metropolitan dynamics than SUR and the following categorical analyses are thus examined through the 3SLS structure.

To test whether or not time (i.e., the type of recession) matters in determining significant explanatory variables and their directions, the study period of 1990 to 2017 is divided into three sub-periods according to national recessions. Each period starts from a

national peak to next national peak in general according to the National Bureau of Economic Research's business cycle reference dates (see Table 10).

Table 10. Dusiness Cycl	e Reference Dates					
Business Cycl	e Reference dates	Duration in Months				
Deele	Turush	Contraction	Expansion			
Peak	Trough	This Peak to This Trough	This Trough to Next Peak			
July 1990	March 1991	8	120			
March 2001	November 2001	8	73			
December 2007	June 2009	18	N/A			

Table 10. Business Cycle Reference Dates

The first period for this analysis is January 1990 to March 2001, consisting of 135 months. To fully use available data, January 1990 to June 1990 remain included despite not being technically included in the corresponding business cycle. The second period is March 2001 to December 2007, which includes 82 months. The third is December 2007 to March 2017, the latest month when the data are available, and contains 112 months. For each of these three sub-periods, the growth, instability, and resilience measures are calculated again from the three recession-specific datasets and included as dependent variables in three separate 3SLS models. All MSAs have a valid growth measure and a valid instability measure. However, there are cases where a metropolitan area could not recover its previous peak (i.e., pre-downturn) employment level occurred until the end of the study period. In such cases, the resilience measure does not produce a valid number, resulting in a missing value. Six MSAs during the first period, 61 MSAs in the second period, and 83 MSAs in the third period have a missing value. To avoid a big loss in the number of observations, especially for the second and third periods, these missing values are replaced by zero for regressions.

The same list of explanatory variables used for the analysis of the pooled period is applied to each sub-period model, and results are compared across periods. Variables are collected for the starting year of each period; 1990 for the first period, 2001 for the second period, and 2007 for the third period. All variables share the same data source as used to for the pooled period model. Exceptionally, variables derived from the *1990 Decennial Census* are replaced by those constructed from the *2000 Decennial Census*²⁰ for the second period and those constructed from *American Community Survey 2005-2007 3-year estimates* of the Census Bureau²¹ for the third period for a timelier information. The percent of votes for a Republican candidate for 2001 is based on the 2000 presidential election data and the one for 2007 comes from the 2004 presidential election data set used for the *Dave Leip's Atlas of U.S. Presidential Elections* data,²² the same data set used for the pooled period. After merging the main data with independent variables, data for the first, second, and third periods are limited to 279, 317, and 298 metropolitan areas respectively.

The causes of three national recessions differ. The 1990s' recession is attributable to a combination of the Federal Reserve's restrictive monetary policy in 1988 to reduce inflation, the elimination of tax shelters after the passage of Tax Reform Act of 1986, and the 1990 oil price spike. After the Tax Reform, real estate losses could not be deducted from taxable income. Consequently, real estate investments contracted, real estate prices dropped, and the real estate boom of the 1980s ended. The collapse of dot-com boom ignited the early 2000's recession. The Great Recession in the late 2000s is attributable to the housing bubble followed by the subprime mortgage crisis and the breakdown of multiple financial institutions including

²⁰ Retrieved on August 1, 2017 from https://nhgis.org

²¹ Retrieved on August 1, 2017 from https://www.census.gov

²² Retrieved on November 2, 2017 from http://statisticaldatasets.data-planet.com

Lehman Brothers. Significant variables are not likely to be identical across periods as each period may have its own explanatory factors to some extent. Some variables may show a steady correlation with the dependent variables regardless of time. The comparison of the three sub-models identifies time-invariant and time-variant variables.

2.2. Results

Despite this characteristic difference among the three national recessions, the three periods of this study have explanatory factors in common (see Table 11). A higher percent of construction workers is related to a faster long-term growth regardless of time. The ongoing construction is a good indicator of a vibrant economy and hence this finding may support the argument of path dependence literature. A more frequent experience of a downturn in the given period is related to a less severe employment loss in the face of a downturn and a quicker recovery after the downturn, regardless of time. Its strong influence on employment dynamics is reaffirmed.

Several other variables show statistical significance in two or more periods and their respective signs do not change over time. This directional consistency makes them potential tools for policymakers, despite their statistical insignificance in some periods. A higher percent of persons with college or higher education, a higher poverty rate, and a higher percent of votes to a Republican candidate in the preceding presidential election induce faster growth, less employment loss, quicker recovery, or a combination of the three depending on time. The impact of the percent of college education and the percent of votes tend to become stronger in recent years, but that of the poverty rate fades out in recent years. Growth was related to a lower percent of Black residents until late 2000s, but such a relationship no longer exists in recent

years. A higher unemployment rate prevents growth, worsens employment loss, and prevents recovery. A more diverse industrial mix represented by a higher Herfindahl index makes metropolitan areas lose more employment during downturns.

Interesting results come next. A few variables are significant in more than two recessions and their signs are the opposite across the corresponding recessions. Such variables might look statistically insignificant at first due to their fluctuating directions over time. Rather, they explicitly address the change in labor markets and societies. The percent of foreign-born persons in a metropolitan area slowed down growth, exacerbated employment loss in the face of a downturn, and slowed down the speed of recovery in the 1990s. However, its relationship with growth has become positive since the 2000s. Although a higher percent of foreign-born persons has intensified the employment loss during the 2001-2007 recession, it has indeed mitigated the loss in the later period of 2007-2017. This variable has a positive relationship with resilience during the 2007-2017 period. Clear is the tendency of being a negative factor in the past to becoming a positive contributor in recent years. The change in beta coefficients over time across equations also supports the gradual transition from a definite negative to a slight negative, to a slightly positive, and to a clear positive. The existence of right-to-work laws in a state contributes to growth until late 2000s, but its role changes to exacerbating employment loss and speeding up recovery in the 2007-2017 period. The role of right-towork laws has changed from positive to mixed. To prevent this transition from settling in the negative in the coming years, the laws may need to reflect the changes in labor market and open to necessary adjustments. A higher percent of manufacturing employees decreases growth in the 2000s but increases growth in the 2010s. A more amount of total asset per employee held by firms in a metropolitan area exacerbates employment loss in

the 1990s but mitigates the loss in the 2000s. Relatively smaller dot-com companies that collapsed in the 2000s are reflected here. This finding implies in general that big established firms were more prone to downturns in the 1990s than the 2000s.

More long-term debt held by local governments induces growth in the 2007-2017 period. More total cash and securities held by local governments lowers employment loss in the same period. They are not statistically significant in any equation prior to 2007. That their positive relationship with the labor market dynamics is present in the latest time only implies that the operative role of governments' use of funds in forming strong labor market dynamics has been small in the past but is now substantial. On the other hand, a higher number of patents per employee and more amount of investment per employee slow down growth in the 1990s and the 2010s respectively. More amount of asset per employee exacerbate employment loss in the 1990s. Although the amount of asset per employee seems to mitigate employment loss in the 2000s, private sector finance in general is not a contributing factor to a healthy labor market.

Standardized coefficients show which of the above statistically significant variables have greater impacts on the change in growth, instability, and resilience measures. The percent of construction employees has had a meaningful influence on growth throughout the study period. The percent of college or higher education had its greatest influence on growth in the 1990s and again in the 2010s. The percent of Black residents and the poverty rate were among the greatest influences on growth in the 1990s, but it appears their degree of influence has declined during the 2000s and they even lose their statistical significance in the 2010s. The short-run vacillations are largely determined by the number of downturns a metropolitan area has experienced over the study period. This variable is unarguably the most significant

influence on instability and resilience regardless of national recessionary periods. Instability was shaped largely by the percent of foreign-born persons and the poverty rate in the 1990s and by the educational attainment in the 2010s.

An iterated model gives more accurate estimates but not all models converge. This categorical model has not converged and thus non-iterated parameter estimates are reported in Table 11. The reduction in the number of statistically significant regressors and the accuracy of coefficients, caused by the failure of convergence, is however believed to be minimal as Table 9 has shown earlier.

		1990-2001			2001-2007			2007-2017	
	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta
Growth									
invcapt	6.48E-09	1.29E-08	0.0256	-3.58E-09	4.68E-09	-0.0283	-2.86E-09**	1.20E-09	-0.0731
ltdot	1.37E-07	1.37E-07	0.0453	-5.24E-08	1.00E-07	-0.0156	1.45E-07**	5.95E-08	0.0738
patent	-2.2457†	1.4864	-0.0825	0.2840	0.6815	0.0165	-0.0269	0.3465	-0.0026
cons	0.0021***	0.0005	0.2832	0.0032***	0.0003	0.3780	0.0011***	0.0002	0.3001
manu	3.58E-05	0.0001	0.0243	-0.0003***	0.0001	-0.1546	0.0002***	0.0001	0.1865
black	-0.0004***	0.0001	-0.3128	-0.0001***	4.80E-05	-0.1159	1.84E-05	2.97E-05	0.0246
foreign	-0.0003*	0.0002	-0.1135	0.0002*	0.0001	0.0914	0.0003***	0.0001	0.2214
coll	0.0005***	0.0001	0.4015	0.0001	0.0001	0.0538	0.0003***	4.55E-05	0.3068
minwage	0.0003	0.0006	0.0311	0.0001	0.0003	0.0212	-0.0002	0.0002	-0.0408
emptax	0.0024	0.0020	0.0717	0.0041**	0.0020	0.0856	0.0006	0.0012	0.0206
right	0.0047***	0.0016	0.1957	0.0016†	0.0012	0.0631	0.0001	0.0007	0.0089
unemp	-0.0013**	0.0006	-0.1837	-0.0002	0.0004	-0.0214	1.77E-05	0.0002	0.0036
pov	0.0010***	0.0002	0.3815	0.0003*	0.0002	0.1067	0.0001	0.0001	0.0316
repub	0.0002***	0.0001	0.1411	0.0001	0.0001	0.0792	0.0001***	3.42E-05	0.1438
instability	-0.1330	0.1300	-0.1323	-0.1528***	0.0466	-0.2585	-0.1603***	0.0312	-0.4774
resilience	-0.0921	0.1215	-0.1522	0.2696*	0.1471	0.3760	0.1597*	0.0839	0.2414
_cons	-0.0304***	0.0089	0.0000	-0.0273***	0.0066	0.0000	-0.0284***	0.0048	0.0000
Instability									
asset	7.39E-09†	5.59E-09	0.0646	-8.62E-09**	3.75E-09	-0.1001	5.74E-10	2.70E-09	0.0093
cst	-7.97E-07	7.98E-07	-0.0705	-2.33E-07	2.95E-07	-0.0325	-5.03E-07*	2.57E-07	-0.0763
herf	0.0591	0.0473	0.0756	0.1181**	0.0537	0.1153	0.0945*	0.0546	0.0895
gov	0.0002	0.0001	0.0820	-0.0002	0.0002	-0.0506	-2.20E-05	0.0003	-0.0048
black	4.67E-06	0.0001	0.0039	-3.57E-05	0.0001	-0.0166	-4.50E-05	0.0002	-0.0202
foreign	0.0007***	0.0001	0.2800	0.0005***	0.0002	0.1594	-0.0007*	0.0004	-0.1929
coll	-0.0001	0.0001	-0.1063	0.0001	0.0001	0.0240	-0.0008**	0.0003	-0.2925
minwage	-2.47E-05	0.0005	-0.0029	-0.0013**	0.0006	-0.1192	0.0010	0.0008	0.0876
emptax	-0.0043**	0.0019	-0.1268	-0.0053	0.0043	-0.0647	-0.0035	0.0062	-0.0394
right	-0.0014	0.0016	-0.0609	-0.0013	0.0028	-0.0295	0.0092***	0.0034	0.1962
unemp	0.0018***	0.0006	0.2585	0.0010	0.0009	0.0789	0.0016†	0.0011	0.1116

Table 11. Three-Stage Least Squares Estimates by National Recession

		1990-2001			2001-2007			2007-2017	
	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta
pov	-0.0007**	0.0003	-0.2799	-0.0007†	0.0005	-0.1230	3.77E-05	0.0004	0.0062
repub	1.07E-05	0.0001	0.0082	0.0001	0.0002	0.0438	-0.0004*	0.0002	-0.1667
span	-0.0025***	0.0006	-0.4247	-0.0058***	0.0008	-0.3874	-0.0137***	0.0017	-0.6212
growth	-0.4142*	0.2284	-0.4165	-0.6469***	0.2038	-0.3823	-2.3385***	0.6252	-0.7851
resilience	0.2820†	0.2198	0.4684	-0.0090	0.3378	-0.0074	2.2942***	0.4581	1.1646
_cons	0.0170**	0.0080	0.0000	0.0252*	0.0136	0.0000	0.0755***	0.0259	0.0000
Resilience									
stdot	-5.81E-06	1.56E-05	-0.0220	1.37E-06	7.93E-06	0.0091	-1.37E-06	2.68E-06	-0.0134
tir	-5.88E-07	4.31E-06	-0.0075	-5.00E-08	1.16E-06	-0.0023	1.99E-07	6.73E-07	0.0099
self	0.0003	0.0009	0.0275	0.0003	0.0007	0.0305	0.0003	0.0002	0.0360
black	-2.76E-05	0.0002	-0.0140	0.0001	0.0001	0.0433	-9.77E-07	0.0001	-0.0009
foreign	-0.0007**	0.0003	-0.1778	0.0002	0.0002	0.0654	0.0002*	0.0001	0.1167
coll	0.0003†	0.0002	0.1247	-0.0001	0.0001	-0.0292	0.0001	0.0001	0.0869
minwage	0.0004	0.0011	0.0267	-1.16E-05	0.0007	-0.0013	-0.0002	0.0003	-0.0322
emptax	0.0019	0.0038	0.0345	0.0046	0.0046	0.0687	0.0007	0.0024	0.0155
right	0.0031	0.0032	0.0797	0.0028	0.0029	0.0777	-0.0026*	0.0014	-0.1074
unemp	-0.0016†	0.0011	-0.1362	0.0002	0.0010	0.0178	-0.0002	0.0004	-0.0245
pov	0.0004	0.0004	0.1053	-0.0003	0.0004	-0.0702	-0.0001	0.0002	-0.0449
repub	2.45E-05	0.0002	0.0113	0.0004***	0.0001	0.2193	0.0001†	0.0001	0.0947
span	0.0043***	0.0009	0.4390	0.0019†	0.0013	0.1521	0.0037***	0.0008	0.3344
growth	0.6817*	0.3621	0.4127	0.3881*	0.2268	0.2783	1.2131***	0.1837	0.8023
instability	0.9313***	0.3573	0.5607	0.1065	0.1887	0.1292	0.2698***	0.0622	0.5314
_cons	-0.0255*	0.0152	0.0000	-0.0152	0.0143	0.0000	-0.0172*	0.0101	0.0000
n		279			317			298	
R^2 (Growth)		0.4117			0.6809			0.7764	
R^2 (Instability)		0.3932			0.5264			0.1657	
R^2 (Resilience)		0.1507			0.2029			0.5689	

Notes. The coefficients and standard errors are rounded up to four significant figures. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test. † indicates statistical significance at the 90% level under the one tailed test.

The unemployment rate (unemp) is highly correlated (0.7274) with the percent of residents in poverty (pov) in the 2001-2007 period, but both variables remain included in the 2001-2007 model to ensure consistency across models.

3. Trend by Census Regions

3.1. Data and Methods

The spatial distribution of the three indices captured in Chapter 2 goes beyond the boundary of a metropolitan area or even a state. Their trends spread out across several states. This finding brings a question of whether or not the set of independent variables acts homogeneously across geographical entities broader than a metropolitan area. Furthermore, variations are likely to exist across those broader geographic entities (Webber, Healy, & Bristow, 2018) and may be strong enough to influence the model. This section tests whether or not heterogeneity is present in employment dynamics.

The 382 Metropolitan Statistical Areas are part of 50 states, the 50 states and District of Columbia constitute 9 Census Divisions, and the 9 Census Divisions are subdivisions of 4 Census Regions. The Census Regions – Northeast, Midwest, South, and West – are the largest official geographic entity that subdivides the United States although they exclude Puerto Rico and island areas outside of Hawaii. Among these geographical entities that are broader than a metropolitan area, states are not expected to offer much extra meaning beyond that for metropolitan areas as some states include few metropolitan areas. Culturally and economically speaking, Census Regions are more intuitive than are Census Divisions and, hence, suggest more beneficial findings. So, I selected the four Census Regions for categorical analysis in this section.

The χ^2 test has been performed on the pooled data, used to produce Table 8, to statistically confirm the existence of heterogeneity across the four Census Regions. The independent variables of the growth equation have different impacts on the Census Regions at the 99% confidence level and those of the resilience equation barely pass the 95% confidence

level as shown in Table 12. This result suggests that it is worth running the model for four subregions of the nation and comparing estimates across the regions.

 $p > \chi^2$ χ^2 df Growth 3 14.73 0.0021 3 Instability 4.03 0.2579 Resilience 3 7.43 0.0594

Table 12. Test of Heterogeneity across Census Regions, by Equation

The model structure, including the dependent and independent variables, is identical to the 3SLS model used for the analysis of the entire nation. The identical model is run by the four census regions and their results are compared across regions. The models of Northeast, Midwest, South, and West Each include 41, 73, 109, and 56 metropolitan areas, respectively.

The comparison of the four sub-models help identify region-invariant and regionvariant variables. It is anticipated that some variables will show a steady correlation with the dependent variables across regions while each region will have its own explanatory factors to some extent. The economy of the West depends less heavily on manufacturing than do the others. The proportion of manufacturing employees within the West region as of 1990 (13%) is only two thirds of that in the Midwest (21%). The percent of manufacturing employment is expected to be a region-variant variable. Another eyecatching difference among regions is the remarkably higher percent of foreign-born persons in the West (8%) which is much higher than that of the other regions (4% in Northeast, 2% in Midwest, and 3% in South). This signals it as another factor with an impact that varies across regions.

3.2. Results

The non-iterated parameter estimates reported in Table 13 show that the majority of statistically significant variables fall into one of the two types. First, some variables show statistical significance in more than two regions, and their coefficients show the same direction in all of those regions. Second, some variables show statistical significance in more than two regions, and their coefficients display an opposite direction in part of those regions.

A possible set of nationwide policies may be constructed by focusing on regioninvariant statistically significant variables. Such variables are defined as those that show significance in two or more regions, and their signs are identical across the corresponding regions. When the four regions are controlled in this categorical structure, the minimum wage pops up as an effective policy tool for a healthy labor market. A higher minimum wage is related to faster growth, a stable market, and resilient recovery. A higher poverty rate at the onset of the study period plays the same role as a higher minimum wage. Its positive association with the indices has been confirmed by both the nationwide model and this regional model. This finding implies that an area with a higher percent of poor residents does not necessarily have a disadvantageous growth pattern. Rather, these people may be a driver for growing, stable, and resilient economy, as they are the ones who are most willing to work in adverse work conditions. Policies to secure and improve a work environment for this group not only benefit these individuals but also the broader labor market. Lastly, a lower unemployment rate is related to faster growth and a more stable economy. A metropolitan area that already suffers from a high unemployment rate is expected to lose even more employment when it is hit by a downturn. Interestingly, all of the three region-invariant variables are related to those who are in the lowest class of the economy: those who earn minimum wage, are in

poverty, or are unemployed. This result stresses that an action against a weak labor market should target this population to be effectual nationwide.

A few additional variables turn out to be region-invariant, albeit related to only one of the three indices, unlike the minimum wage, the poverty rate, and the unemployment rate. A higher state average employer tax rate is associated with faster long-term growth. A more active preparation of state for unemployment benefits may be viewed as a burden on the employer side but contributes to the long-run increase in the number of employees, which benefits employers in turn. The public intervention to ensure the minimal safety net through the unemployment benefit taxation is advantageous to both employees and employers. A higher percent of votes for a Republican presidential candidate in the preceding election is also associated with faster long-term growth. Metro areas with a stronger Republican stance could have been offered greater financial assistance from the federal government or a more favorable business environment under Republican administrations. Given that this favor for Republican areas is likely reverted when the Democratic administration takes over, the positive correlation between the percent of votes for a Republican candidate and long-term growth may imply that the financial support for Republican areas by the Republican administrations is stronger than that for Democratic states by the Democratic administration. Alternatively, as the data used here is from the 1988 presidential election in which George H. W. Bush won, a higher percent of votes for him may simply reflect a stronger political stance of residents (i.e., workers) in an MSA. Such an explicitly represented stance may somehow relate to the expansion of existing firms in the MSA or attract businesses or workers outside the MSA, leading to faster longterm growth. The exact explanation on the relationship between the political opinions of workers and the long-term labor market dynamics is what future research may uncover. More total asset per employee held by firms within a metropolitan area and more frequent experience with downturns for the given time mitigate employment loss in the face of a downturn. Firms with a more affluent financial resource may endure downturns longer without immediate mass dismissal. The vaccinating role of frequent experience of downturns is confirmed again here. A diverse industrial structure represented by a higher Herfindahl index, however, is shown to negatively affect stability. The advice of not putting all eggs into one basket does not apply to metropolitan labor markets. A simple combination of various industries does not necessarily prevent a labor market from breaking down in crises. This may be because a large portion of industries are intertwined and the shock from an industry spreads to related industries.

Some variables show inconsistent signs across regions where they show statistical significance. The growth equation tends to distinguish the West from the rest, especially the Northeast. A lower percent of Black residents, a higher percent of foreign-born persons, and a higher percent of persons with college or higher education induce growth in the Northeast but prevent growth in the West. The Midwest and South tend to follow Northeast trends. The instability equation on the other hand does not show an explicit trend across regions. A lower percent of Black residents stabilizes the labor market in the South while worsening employment loss in the West. A higher percent of foreign-born population alleviates the loss in the Midwest, while it counteracts the lessening in the Northeast and West. A higher percent of government workers alleviates employment loss in the South, but surprisingly exacerbates the loss in the Northeast and Midwest. A higher percent of votes for a Republican candidate is positively related to stability in the West and negatively related in the Northeast and Midwest.

Lastly, the resilience equation somewhat shows the Northeast versus Midwest trend. More per capita short-term debt by local governments and a higher unemployment rate are associated with quick recovery in the Northeast but linked to slow recovery in the Midwest.

Variables that differentiate one region from others are those that show statistical significance in only one of the four regions. Most of them distinguish the Northeast from others. The number of patents produced per employee and the percent of construction workers show positive relationships with growth. The per capita cash and securities hold by local governments, the percent of residents with college or high education, and the state employer tax rate negatively influence stabilization of employment against downturns. The per capita total intergovernmental revenue shows a negative relationship with resilience. Along with the percent of manufacturing workers inducing growth in the West, the percent of Black residents, the percent of foreign-born residents, and the number of downturns an MSA experiences for the past 25 years determine the Western resilience. In the Midwest, the existence of right-to-work laws in a state increases its long-term growth but aggravates employment loss in a crisis. Whether to endure the short-run rigidity for long-run growth or the slow long-run growth for short-run flexibility thus becomes a state's choice.

In addition, the resilience model shows remarkably higher validity in the West. Accompanied by the fact that several variables of the growth model show an opposite direction in the West compared to the rest of the nation, this finding implies that the West economy has a unique apparatus for resilience. Whether it is their industrial composition of depending less on manufacturing and relying more on technology, their diverse population composition of embracing all races, the business environment for their firms, or a combination of all of these elements has made this region special within the nation. Their lighter dependency on manufacturing, compared to other regions, is found to positively relate to growth of the region, implying that they are on the right path in this sense. But their relatively high share of foreignborn population is proven to decrease growth, exacerbate loss, and slow down recovery of the region. Foreign-born persons in the United States are likely to be less connected to the region and are willing to move across regions and even nations for jobs, than U.S. citizens. This characteristic may cause the determinate adverse link between the foreign-born persons and the employment dynamics in the West whose labor market contains a remarkably high proportion of foreign-born person within the nation.

The relative strength of the predictors, represented by the standardized coefficients, reveals that the proportion of foreign-born population, that of Black population, the unemployment rate, and the poverty rate have strong impacts on the Western economy. These variables are also strong in the Midwest but their overall impacts are smaller here than in the West. The state average employer tax rate stands out in the Northeast.

	N	Northeast			Midwest			South			West	
	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta
Growth												
invcapt	-1.51E-08***	5.61E-09	-0.0800	-6.65E-09	6.72E-09	-0.0351	2.53E-08†	1.85E-08	0.1337	4.62E-08	4.94E-08	0.244
ltdot	-9.56E-09	4.17E-07	-0.0042	4.25E-07	5.70E-07	0.1879	3.17E-07	4.21E-07	0.1399	2.93E-08	9.27E-08	0.012
patent	1.4806*	0.7983	0.0728	-0.6450	0.9270	-0.0317	0.0861	2.4585	0.0042	-0.8620	6.0053	-0.042
cons	0.0005*	0.0003	0.0846	0.0005	0.0008	0.0878	0.0005	0.0004	0.0892	0.0007	0.0007	0.132
manu	-2.74E-05	0.0001	-0.0249	0.0001	0.0001	0.0866	-0.0001	0.0001	-0.1190	-0.0003*	0.0002	-0.283
black	-0.0002**	0.0001	-0.1955	-0.0003**	0.0001	-0.3351	-0.0001	0.0001	-0.0632	0.0010**	0.0005	1.137
foreign	0.0004***	0.0001	0.2374	-0.0003	0.0004	-0.1576	0.0003†	0.0002	0.1575	-0.0011***	0.0002	-0.596
coll	0.0002***	0.0001	0.1624	0.0002*	0.0001	0.2139	0.0001	0.0002	0.1336	-0.0003†	0.0002	-0.27
minwage	-0.0017	0.0020	-0.2687	0.0048**	0.0024	0.7612	0.0002	0.0007	0.0346	0.0020**	0.0010	0.326
emptax	0.0059***	0.0012	0.2323	0.0019	0.0022	0.0761	0.0079†	0.0050	0.3100	0.0006	0.0026	0.022
right	(omitted)	(omitted)	0.0000	0.0035**	0.0017	0.1984	-0.0023	0.0023	-0.1287	0.0002	0.0032	0.014
unemp	0.0002	0.0004	0.0425	-0.0009†	0.0007	-0.1733	-0.0011†	0.0009	-0.2127	-0.0037***	0.0012	-0.70
pov	-0.0001	0.0001	-0.0793	0.0002	0.0003	0.1070	0.0005*	0.0003	0.2913	0.0015***	0.0005	0.823
repub	0.0002***	0.0001	0.1852	0.0001*	0.0001	0.1439	5.26E-06	0.0001	0.0054	0.0007***	0.0001	0.684
instability	-0.1463***	0.0217	-0.3758	-0.0636†	0.0443	-0.1633	-0.1556**	0.0772	-0.3998	0.3540***	0.1095	0.909
resilience	-0.0450	0.0665	-0.0536	-0.2278**	0.1070	-0.2711	0.9596***	0.2470	1.1420	-0.2278	0.1809	-0.27
_cons	-0.0106	0.0112	-0.7973	-0.0209†	0.0152	-0.5779	-0.0177	0.0153	0.2971	-0.0059	0.0177	2.53
Instability												
asset	-1.58E-08†	9.74E-09	-0.0715	-2.06E-08†	1.56E-08	-0.0933	-4.23E-08*	2.22E-08	-0.1916	-5.42E-09	2.98E-08	-0.024
cst	6.47E-06†	4.46E-06	0.2965	2.20E-06	2.31E-06	0.1009	-2.97E-07	1.21E-06	-0.0136	-2.67E-07	9.79E-07	-0.012
herf	0.5699***	0.1882	0.3779	0.4799***	0.1417	0.3182	0.4314***	0.1016	0.2860	0.2389*	0.1226	0.15
gov	0.0012**	0.0005	0.2875	0.0009†	0.0006	0.2293	-0.0008***	0.0003	-0.1882	-0.0002	0.0002	-0.061
black	-0.0005	0.0005	-0.2380	0.0007	0.0007	0.3105	0.0002†	0.0001	0.0932	-0.0016**	0.0008	-0.71
foreign	0.0009†	0.0006	0.1929	-0.0018†	0.0013	-0.3909	-4.69E-05	0.0004	-0.0100	0.0016***	0.0004	0.33
coll	0.0006*	0.0003	0.2496	-0.0003	0.0005	-0.1237	-0.0003	0.0003	-0.1178	0.0003	0.0003	0.12
minwage	0.0063	0.0111	0.3944	0.0064	0.0083	0.3993	-0.0016†	0.0010	-0.0974	-0.0029*	0.0016	-0.17
emptax	0.0225***	0.0083	0.3446	-0.0004	0.0063	-0.0068	-0.0065	0.0078	-0.0993	-0.0008	0.0040	-0.01
right	(omitted)	(omitted)	0.0000	0.0116*	0.0064	0.2535	-0.0004	0.0040	-0.0087	0.0008	0.0046	0.01
unemp	0.0035*	0.0020	0.2600	0.0062**	0.0024	0.4567	0.0011	0.0015	0.0791	0.0067***	0.0020	0.49

Table 13. Three-Stage Least Squares Estimates by Census Region

	Ν	Northeast			Midwest			South			West	
-	Coef.	Std. Err.	Beta									
pov	-0.0030***	0.0008	-0.6325	-0.0021*	0.0011	-0.4433	-0.0004	0.0006	-0.0748	-0.0024***	0.0008	-0.4983
repub	0.0008***	0.0003	0.3252	0.0005†	0.0003	0.1801	-2.68E-05	0.0002	-0.0106	-0.0005*	0.0003	-0.1830
span	-0.0024***	0.0008	-0.3227	-0.0019***	0.0007	-0.2514	-0.0022***	0.0005	-0.3036	-0.0021***	0.0005	-0.2782
growth	-4.2261***	0.7972	-1.6450	-1.8473*	1.0242	-0.7190	-0.4493	0.3525	-0.1749	-0.0583	0.4643	-0.0227
resilience	0.3998	0.6092	0.1852	0.6012*	0.3455	0.2785	0.3963	0.5037	0.1836	1.2868***	0.1895	0.5961
_cons	-0.1338**	0.0596	-1.7750	-0.0630†	0.0460	-0.1383	0.0275†	0.0209	-0.2302	-0.0103	0.0230	-1.2071
Resilience												
stdot	3.61E-05**	1.60E-05	0.2541	-3.74E-05†	2.88E-05	-0.2633	5.77E-06	1.60E-05	0.0407	5.89E-06	1.09E-05	0.0414
tir	-8.49E-06†	5.16E-06	-0.2021	8.22E-06	6.82E-06	0.1956	3.46E-06	4.65E-06	0.0822	-1.04E-06	3.46E-06	-0.0249
self	0.0005	0.0011	0.0793	-0.0011	0.0010	-0.1858	0.0006	0.0007	0.0922	0.0003	0.0005	0.0410
black	0.0001	0.0003	0.1114	-0.0005	0.0004	-0.4520	1.97E-05	0.0001	0.0185	0.0013*	0.0007	1.2643
foreign	-0.0003	0.0005	-0.1175	-0.0007	0.0010	-0.3235	-0.0002	0.0003	-0.0937	-0.0011***	0.0004	-0.5084
coll	-0.0001	0.0002	-0.0774	0.0002	0.0003	0.1544	-0.0001	0.0002	-0.0565	-0.0002	0.0002	-0.1426
minwage	0.0130†	0.0100	1.7528	0.0102†	0.0062	1.3727	-0.0001	0.0008	-0.0127	0.0021*	0.0012	0.2791
emptax	-0.0025	0.0061	-0.0827	0.0051	0.0049	0.1700	-0.0045	0.0059	-0.1498	-0.0010	0.0030	-0.0338
right	(omitted)	(omitted)	0.0000	0.0067	0.0055	0.3182	0.0021	0.0027	0.1007	0.0007	0.0033	0.0325
unemp	0.0025**	0.0012	0.4052	-0.0045***	0.0015	-0.7270	0.0004	0.0010	0.0562	-0.0045***	0.0016	-0.7161
pov	-0.0001	0.0005	-0.0234	0.0011†	0.0007	0.4843	-0.0003	0.0003	-0.1438	0.0015**	0.0006	0.6907
repub	0.0002	0.0002	0.1486	0.0003	0.0002	0.2262	1.22E-05	0.0002	0.0104	0.0003	0.0002	0.2293
span	0.0005	0.0005	0.1509	0.0003	0.0004	0.1008	0.0003	0.0003	0.0909	0.0016***	0.0004	0.4549
growth	0.6332	0.7507	0.5320	-1.6889**	0.7168	-1.4192	0.7364***	0.2444	0.6188	0.0316	0.3587	0.0266
instability	-0.1228	0.1266	-0.2650	0.0555	0.1286	0.1197	0.2490**	0.1006	0.5375	0.6320***	0.1079	1.3643
_cons	-0.0557	0.0455	-1.2395	-0.0130	0.0352	-1.1641	0.0046	0.0164	-0.0898	-0.0013	0.0151	2.0484
n		41			73			109			56	
R^2 (Growth)		0.8554			0.6460			-0.2770			0.3718	
R^2 (Instability)		0.8270			0.8453			0.6144			0.6688	
R^2 (Resilience)		0.2717			0.0110			0.1849			0.4625	

Notes.

The coefficients and standard errors are rounded up to four significant figures. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test. † indicates statistical significance at the 90% level under the one-tailed test.

4. Trend by Labor Market Scales

4.1. Data and Methods

A large dense population identifies a metropolitan statistical area and grants it an identity distinct from the rest of the nation. A substantial difference still exists in the scale of economy among metropolitan areas. The data for this study includes a metropolitan area of 6,343 employees (The Villages, FL) through a metropolitan area of 7,892,300 employees (New York-Newark-Jersey City, NY-NJ-PA).²³ These two MSAs are less likely to be directly compared one another, as the socioeconomic structure of a gigantic metropolis is different from that of an area barely meeting the minimal size requirement to be an MSA.

The impact of scale on labor market dynamics is tested here by incorporating the labor market scale of metropolitan areas. Two potential methods exist to perform the test. One may include the raw employee counts of each metropolitan area to the independent variable list, which informs changes in the three indices when an area's total employees change by one unit. Or, one may classify metropolitan areas by their labor market size and run separate regressions, which identifies factors that act differently by economy scales if any. Despite the unavoidable inclusion of arbitrary grouping, the ability to check heterogeneity is expected to give more meaningful findings than does the influence of an extra employee on the three indices. Thus, I have selected the latter approach to analyze the impact of scale on economy.

The total number of MSAs with valid independent variables after merge remains the same as 279. Half of them have approximately 100,000 employees or less each, and few MSAs share a great portion of national employees (see Table 14). The merits of balancing MSA counts across groups, balancing sums of employees across groups, and using intuitive

²³ These particular figures are non-seasonalized employment counts.

thresholds are simultaneously considered when classifying MSAs. Consequently, all MSAs are divided into three groups according to their employment counts, resulting in metros that have fewer than 100,000 employees, between 100,000 and 500,000, and over 500,000 employees. Each group consists of 123, 116, and 40 MSAs, which are 44%, 42%, and 14% of 279 MSAs respectively. Each contains 6,745,216 employees, 24,281,900 employees, and 57,536,524 employees, respectively.

Population	Count	Percent	Cumulative Percent
< 50,000	55	20	20
50,000 - 100,000	68	24	44
100,000 - 150,000	45	16	60
150,000 - 200,000	25	9	69
200,000 - 250,000	12	4	73
250,000 - 300,000	13	5	78
300,000 - 350,000	5	2	80
350,000 - 400,000	7	3	82
400,000 - 450,000	5	2	84
450,000 - 500,000	4	1	86
500,000 - 550,000	4	1	87
550,000 - 600,000	1	0	87
600,000 - 650,000	4	1	89
650,000 - 700,000	1	0	89
700,000 - 750,000	5	2	91
750,000 - 800,000	1	0	91
800,000 - 850,000	2	1	92
850,000 - 900,000	2	1	93
900,000 - 950,000	0	0	93
950,000 - 1,000,000	2	1	94
>= 1,000,000	18	6	100

Table 14. Distribution of Labor Market Scales

The χ^2 test has been performed on the pooled data, used to produce Table 8, to statistically confirm the existence of heterogeneity across the three labor market scales. The independent variables of the growth and instability equations have different impacts at the 99% confidence level (see Table 15). This result suggests that it is worth comparing and contrasting estimates across the three subgroups.

Table 15. Test of ficterogen	licity across Labor Mari	Ket Scales, by Equation	
	df	χ^2	$p > \chi^2$
Growth	2	10.96	0.0042
Instability	2	7.40	0.0248
Resilience	2	3.85	0.1458

Table 15. Test of Heterogeneity across Labor Market Scales, by Equation

The model structure including the dependent and independent variables is identical to the 3SLS model used for the analysis of the pooled MSAs. The identical model is run by the three groups and their results are compared. The comparison of the three sub-models help identify scale-invariant and scale-variant variables. It is anticipated that some variables will show a steady correlation with the dependent variables across groups while each group will have its own explanatory factors to some extent.

4.2. Results

Most variables are either statistically significant for two or more groups and show an identical direction for all corresponding groups or statistically significant for only one group (see Table 16). The latter in particular suggests the factors to which each group is more sensitive. Large-sized metropolitan areas occupy most of such variables, followed by medium-sized metropolitan areas. Large-sized metropolitan areas report the highest R^2 in all three equations, followed by medium- and, then, small-sized areas. This pattern signals that the quantitative factors become more relevant with scale.

Public and private finance is meaningful mostly in metropolises. As local governments hold more long-term debt per capita and firms invest more capital per employee, a large metropolitan area may experience faster growth, which implies that investment drives long-term metropolitan growth. The positive role of long-term debt is confirmed across all scales of economies. But a higher number of patents granted per employee acts the opposite way, suggesting that the investment is critical but patents may not be central to the investments that induce long-term growth. Unlike the positive relationship between the long-term public debt and growth, the short-term public debt is negatively related to resilience. The short-term debt indicates the area needs urgent financial assistance, while the long-term debt suggests the area has set farsighted investment plans. These counteracting impacts of two types of debts imply that the local governments' financial strength is a basis for maintaining an upward path. In addition, the fact that a more amount of per capita intergovernmental revenue induces resilience implies that the connection to and the financial assistance from other governments in crises are a source for revitalizing lost jobs. For small-sized areas, a more amount of private assets per employee helps reduce job losses in crises.

Industrial composition is meaningful in both small- and large-sized areas, with some variables being statistically significant across all scales. The greater share of construction employees there is, the higher the growth rate is in all three scales. This result proves that those that have active economic activities in the present are expected to keep growing in the future, supporting the argument of path dependency literature. The percent of manufacturing employees induces growth in large-sized areas but prevents growth in small-sized areas. The more concentrated the industrial composition, the less employment is lost in the face of a downturn in all three scales. It is confirmed again that industrial diversity does not contribute to stabilization, probably due to the domino effect of shocks across industries. Or, this positive impact of high concentration may reflect that specialization and agglomeration economies are as effective in practice as described in theories. What contributes to a smaller loss in small- and large-sized areas is a higher share of government employees. Medium-sized areas may be those that are energetically expanding economic activities and hence less susceptible to this insurance factor. The sole industry-related variable showing statistical significance in the resilience equation is the percent of self-employed persons, which is negatively related to resilience in large-sized areas. This could be due to a low share of small businesses in large-sized areas due to the existence of multiple big firms, while the share may be greater in smaller areas. Or, these self-employed may include those that were laid off in the recent past of 1990, indicating that the corresponding areas had already been suffering from adverse economic conditions in 1990. Such a pre-existing adverse condition may be negatively related to upward moves according to the broad discussion of path dependency researchers.

State laws and regulations are represented by three variables including the state minimum wage, the existence of right-to-work laws in the state, and the employer tax rate. These variables are effective in medium- or large-sized metropolitan areas only. A higher minimum wage, a higher employer tax rate, and the existence of right-to-work laws induce growth but hinder resilience in medium-sized metropolitan areas. On the other hand, in large-sized areas, a higher minimum wage slows down growth and resilience, while it alleviates employment loss. The existence of right-to-work laws alleviates employment loss but slows down resilience in these areas. A higher employer tax rate has a positive contribution to metropolises' resilience. A combination of these policy variables indicates that these laws are at least not pivotal in determining employment dynamics of small-sized areas and medium-sized areas experience a mixed effect of fast growth and slow resilience. A secure work environment backed by a higher minimum wage and the right-to-work laws is effective in protecting workers in crises in big metropolitan areas, but blocks both longand short-run upward moves.

Demographic variables have mixed effects across the three economy scales. A lower percent of Black residents induces long-term growth in all three scales and a smaller employment loss in small- and large-sized areas. In medium-sized areas, it rather hinders recovery processes: A higher percent of Black residents increases resilience in these areas. Foreign-born residents also show a conflicting impact across metropolitan sizes. In small metropolitan areas, a lower percent of foreign-born persons is preferred to attain a faster growth and a smaller employment loss. In large-sized areas, a lower percent is preferred for growth but a higher percent is needed for resilience. A higher percent of college or higher education induces the long-term growth in all three scales but these highly educated workers are subject to job loss in medium-sized areas in crises.

With respect to economic variables, a lower unemployment rate induces growth and minimizes employment loss in small- and medium-sized areas, and increases largesized areas' resilience. This finding implies that a good labor market condition at the onset of the study period is in general an indicator of growing, stable, and resilient path. A higher poverty rate induces growth in small- and medium-sized areas, and is associated with a smaller loss of employment over the period of downturns and recoveries in small-sized areas. The relationship fading out as the economy scale increases implies that larger areas may have a smaller share of those in poverty or have no marginal jobs for these people, invalidating their statistical significance.

A higher percent of votes for the Republican party induces growth in any scale, which has been identified multiple times in previous regressions. On the other hand, it shows a negative influence on minimizing job losses in medium-sized areas and returning to the pre-downturn level in medium- and large-sized areas. Once a new administration steps in, the political stance to receive the administration's favor changes. The federal aid allocated in favor of Republican areas can thus be reversed under a Democratic administration. Such changes may be captured in short-run (instability and recovery) rather than long-run (growth), resulting in a negative impact on stabilization and resilience. The continued positive relationship with growth may reflect that the favor of Republican areas has been greater or lasted longer than that of Democratic areas over the study period. Or, as the scale of economy increases, the ability to maintain and recover jobs may depend less on the political stance and rely more on other aspects, and even convert the effect of Republican stance from positive to negative.

Lastly, a more frequent experience of a downturn in a given period helps metropolitan areas of any scale reduce their employment loss and leads small and mediumsized areas to a quick return to their pre-downturn levels. How metropolitan areas prepare themselves after *each* downturn would be one of the most interesting topics to be uncovered in future research.

The standardized coefficients convey an interesting finding. The relatively strong variables vary greatly across labor market scales, meaning that as the economy of a metropolitan area expands it becomes influenced by new predictors. The percent of foreign-born population, the unemployment rate, the poverty rate, and the frequency of experiencing downturns are critical when a metropolitan area has fewer than 100,000 employees. When the metropolitan area passes this threshold, it becomes less influenced by the proportion of foreign-born population or the unemployment rate. Instead, the existence of

right-to-work laws in a state and the political stance of its residents become influential. Once the area reaches the threshold of 500,000 employees, the public finance including the longterm debt and the intergovernmental revenue becomes a strong regressor, along with the educational attainment, the racial composition, the industrial composition. The minimum wage also becomes meaningful in metropolises. Interestingly, the frequency of experiencing downturns loses its importance as the economy scale grows. This implies that relatively small emerging metropolitan areas are apt to learn from each downturn and better prepare themselves for an upcoming downturn, while metropolises have already gone through multiple downturns and their economies now depend on more clearly expressed factors such as demographic variables and the utilization of public finance rather than learning-by-experiencing.

The previous categorical analyses by national recession and Census Regions have resulted in differences across subgroups, but the trends across subgroups have not been as distinguishable as what is discovered in this section. The examination of employment dynamics along with the scalar evolution of areas in future research is thus expected to open up more interesting stories.

	Sm	all-Sized Econor	ny	Med	ium-Sized Econo	omy	Lar	ge-Sized Econor	ny
	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta
Growth									
invcapt	-5.10E-09	1.36E-08	-0.0269	5.78E-09	1.01E-08	0.0306	4.75E-08**	1.89E-08	0.2508
ltdot	2.07E-07*	1.09E-07	0.0914	4.57E-07*	2.54E-07	0.2018	1.73E-06***	6.19E-07	0.7629
patent	0.8935	1.4754	0.0439	-0.0869	1.2960	-0.0043	-5.2280**	2.4554	-0.2570
cons	0.0017***	0.0004	0.3139	0.0005†	0.0003	0.0955	0.0021***	0.0006	0.3797
manu	-0.0003*	0.0002	-0.2815	-0.0001	0.0001	-0.0878	0.0004**	0.0002	0.3729
black	-0.0003***	0.0001	-0.3251	-0.0002***	0.0001	-0.1909	-0.0004***	0.0001	-0.3962
foreign	-0.0010***	0.0004	-0.5586	3.88E-05	0.0001	0.0213	-0.0001*	0.0001	-0.0687
coll	0.0003*	0.0001	0.2535	0.0001†	0.0001	0.1137	0.0004***	0.0001	0.3897
minwage	0.0010	0.0008	0.1631	0.0013**	0.0005	0.2009	-0.0011†	0.0007	-0.1701
emptax	0.0017	0.0023	0.0675	0.0041***	0.0016	0.1602	-0.0001	0.0020	-0.0058
right	-3.02E-06	0.0018	-0.0002	0.0054***	0.0014	0.3024	-0.0001	0.0020	-0.0044
unemp	-0.0023***	0.0008	-0.4354	-0.0008†	0.0005	-0.1459	-0.0004	0.0009	-0.0786
pov	0.0010***	0.0003	0.5557	0.0007***	0.0002	0.3631	0.0004	0.0004	0.2284
repub	0.0001†	0.0001	0.1438	0.0002***	0.0001	0.2497	0.0002**	0.0001	0.2207
instability	0.0359	0.0669	0.0923	-0.1379***	0.0458	-0.3542	-0.1047***	0.0381	-0.2689
resilience	0.5055**	0.2205	0.6015	0.4657***	0.1285	0.5542	0.0920	0.0991	0.1095
_cons	-0.0257***	0.0094	-0.3113	-0.0284***	0.0081	0.0266	-0.0355***	0.0087	0.1679
Instability									
asset	-2.96E-08*	1.71E-08	-0.1341	-1.36E-09	8.47E-09	-0.0061	4.94E-10	2.71E-08	0.0022
cst	-1.47E-06	1.35E-06	-0.0673	-3.44E-07	9.62E-07	-0.0158	2.19E-06	2.65E-06	0.1003
herf	0.4391***	0.0837	0.2912	0.3800**	0.1747	0.2520	1.7039***	0.3301	1.1299
gov	-0.0009***	0.0003	-0.2191	0.0001	0.0002	0.0338	-0.0010*	0.0006	-0.2528
black	0.0006***	0.0002	0.2777	-0.0001	0.0002	-0.0360	0.0006*	0.0003	0.2742
foreign	0.0010†	0.0006	0.2088	0.0001	0.0003	0.0283	0.0003	0.0003	0.0595
coll	0.0001	0.0003	0.0570	-0.0002	0.0002	-0.0667	0.0011***	0.0004	0.4378
minwage	-0.0018	0.0015	-0.1112	0.0011	0.0013	0.0713	-0.0062***	0.0019	-0.3834
emptax	-0.0049	0.0046	-0.0745	0.0046	0.0046	0.0700	-0.0031	0.0072	-0.0481
right	-0.0010	0.0036	-0.0219	0.0053	0.0044	0.1158	-0.0182**	0.0076	-0.3982
unemp	0.0051***	0.0013	0.3794	0.0030**	0.0014	0.2229	0.0033	0.0028	0.2445

Table 16. Three-Stage Least Squares Estimates by Labor Market Scale

	Small-Sized Economy			Med	Medium-Sized Economy			Large-Sized Economy		
	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	Coef.	Std. Err.	Beta	
pov	-0.0018***	0.0006	-0.3785	-0.0005	0.0006	-0.0998	0.0012	0.0012	0.2580	
repub	2.78E-05	0.0002	0.0110	0.0003†	0.0002	0.1128	0.0002	0.0004	0.0777	
span	-0.0022***	0.0004	-0.2997	-0.0022***	0.0005	-0.3016	-0.0020*	0.0010	-0.2642	
growth	-0.3536	0.4097	-0.1376	-1.5284***	0.4785	-0.5949	-0.5326	0.5912	-0.2073	
resilience	0.0688	0.3508	0.0319	1.7860***	0.3614	0.8273	-0.3993	0.5084	-0.1850	
_cons	0.0077	0.0164	0.1804	-0.0442*	0.0228	0.0814	-0.1761***	0.0348	-0.0779	
Resilience										
stdot	-1.94E-05	1.67E-05	-0.1367	-3.08E-06	4.71E-06	-0.0217	-3.03E-05†	2.15E-05	-0.2134	
tir	3.02E-06	4.63E-06	0.0718	-8.15E-07	1.78E-06	-0.0194	1.34E-05***	4.45E-06	0.3189	
self	5.28E-06	0.0007	0.0009	0.0003	0.0003	0.0538	-0.0044***	0.0014	-0.7255	
black	2.42E-05	0.0002	0.0229	0.0001*	0.0001	0.1414	-0.0001	0.0002	-0.1246	
foreign	0.0005	0.0004	0.2370	-0.0001	0.0002	-0.0405	0.0003*	0.0002	0.1370	
coll	5.33E-06	0.0002	0.0045	1.44E-05	0.0001	0.0122	-0.0001	0.0002	-0.0655	
minwage	-0.0004	0.0010	-0.0546	-0.0011*	0.0006	-0.1482	-0.0014†	0.0010	-0.1907	
emptax	0.0026	0.0035	0.0854	-0.0047**	0.0020	-0.1548	0.0087**	0.0034	0.2867	
right	0.0014	0.0028	0.0643	-0.0049**	0.0020	-0.2316	-0.0047†	0.0036	-0.2200	
unemp	2.63E-05	0.0011	0.0042	-0.0002	0.0006	-0.0274	-0.0043***	0.0016	-0.6823	
pov	-0.0002	0.0004	-0.0993	-0.0004†	0.0003	-0.1700	0.0013*	0.0007	0.5779	
repub	0.0002	0.0001	0.1383	-0.0003***	0.0001	-0.2306	-0.0003†	0.0002	-0.2648	
span	0.0008**	0.0004	0.2423	0.0006***	0.0002	0.1813	0.0005	0.0006	0.1398	
growth	0.2992	0.3094	0.2514	1.0744***	0.1742	0.9028	1.0977***	0.3230	0.9223	
instability	0.1948*	0.1093	0.4206	0.3705***	0.0450	0.7999	0.1300†	0.0886	0.2805	
_cons	-0.0034	0.0149	0.1553	0.0212**	0.0103	-0.0591	0.0480***	0.0183	-0.5514	
n		123			116			40		
R^2 (Growth)		0.4142			0.6328			0.9049		
R^2 (Instability)		0.6543			0.7129			0.8188		
R^2 (Resilience)		0.2567			0.4955			0.6219		

Notes.

The coefficients and standard errors are rounded up to four significant figures. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test. † indicates statistical significance at the 90% level under the one-tailed test.

5. Trend by Author Defined Categories

5.1. Data and Methods

The eight groups classified by medians of the three indices (see Table 4) are the categorical standard for the third categorical analysis. This median-based classification offers a more balanced sample size per group than the U.S. mean-based classification (see Tables 4 and 5) and is deemed more suitable for this analysis. Group 1 represents growing fast, stable, and resilient areas; group 2 represents growing fast, stable, and non-resilient areas; group 3 represents growing fast, unstable, and resilient areas; group 4 represents growing fast, unstable, and non-resilient areas; group 5 represents growing slowly, stable, and resilient areas; group 6 represents growing slowly, stable, and non-resilient areas; group 7 represents growing slowly, unstable, and resilient areas; and group 8 represents growing slowly, unstable, and non-resilient areas. The χ^2 test has been performed on the pooled data, used to produce Table 8, to statistically confirm the existence of heterogeneity across the eight categories. The independent variables of all three equations have different impacts on different categories at the 99% confidence level (see Table 17), confirming the necessity of running the model by category. The fourth and fifth groups contain too few metropolitan areas to produce parameter estimates and are omitted from the analysis.

Table 17. Test of Heterogeneity across Author-Defined Categories, by Equation								
	df	χ^2	$p > \chi^2$					
Growth	7	105.57	0.0000					
Instability	7	46.90	0.0000					
Resilience	7	132.37	0.0000					

Table 17. Test of Heterogeneity across Author-Defined Categories, by Equation

The model structure including the dependent and independent variables is identical to the 3SLS model used for the analysis of the entire nation. The identical model is run by the six groups and their results are compared across groups. After being merged with independent variables, the groups 1, 2, 3, 6, 7, and 8 include 45, 51, 29, 36, 44, and 61 MSAs respectively. The comparison of the six sub-models help identify group-invariant and group-variant variables. Finding a consistent pattern of a variable across groups is likely to be more difficult in this analysis than the preceding categorial regressions, due to a more detailed grouping of metropolitan areas. However, variables that show a steady correlation with the dependent variables across groups may confirm their strong relationship if any.

5.2. Results

Multiple variables have shown opposite signs across groups where they show statistical significance, making it not easy to detect a consistent pattern as expected. Therefore, unlike the way in which the previous regression output has been reported, this section focuses on comprehensive tendencies not each variable.

First of all, the public and private financial status is meaningful in few groups (see Table 18). In accordance with previous regression results, the financial condition at the onset of the study period is not a pivotal factor for determining the following cycle of metropolitan labor markets. Despite being mentioned as part of a central aspect of economic growth and fluctuations in theories, financial variables have not maintained their high position in this empirical test. The sole financial variable without conflicting directions across groups is the per capita long-term debt held by local governments within a metropolitan area. This per capita debt contributes to growth of group 1 (growing fast, stable, and resilient) and group 6 (growing slowly, stable, and non-resilient).

Industrial composition that has been most frequently mentioned in empirical research is significant in only few groups as the public and private financial condition. Industrial diversity represented by a higher Herfindahl index increases instability of group 7 that grows slowly, is unstable, and is resilient, but is not significant in any other groups. Its heavy negative influence derived from preceding regressions has somewhat faded here but never turned positive. The percent of manufacturing employees shows no significance except for its positive influence on growth of group 6 where the employment grows slowly, is stable, and is not resilient. A higher percent of governmental employees is associated with higher instability of group 7, which breaks the assumption that the more the public jobs the stable the labor market.

Instead of the financial and industrial factors, state policies, socioeconomic conditions, and political stance lead the set of influential explanatory variables. A state minimum wage, an employer tax rate, and the existence of right-to-work laws in a state have influences across groups and indices, albeit not having the same direction across groups. A higher minimum wage reduces the growth potential, exacerbates employment loss, and slows down recovery of group 7, and has the same negative influence on growth of group 8 and resilience of group 3. It is found to contribute to the worst performing group (group 8)'s efforts to reduce employment loss and return to its pre-downturn level, but metropolitan areas are classified into this group due to their below-median performance on stabilization and resilience, which implies that a higher minimum wage might mitigate their low performance but is not strong enough to push them to a better performing group. On a positive side, a higher minimum wage is positively related to the best performing group (group 1)'s resilience and the group 6's capability of extenuating employment loss.

A higher employer tax rate also has a mixed effect. It induces growth of groups 2, 7, and 8 but slows down growth of group 6; exacerbates employment loss in groups 1 and 8; and contributes to resilience in groups 3 and 7 but limits resilience of groups 1 and 8. Despite such a mixed consequence, a more liberal business environment driven by a lower employer tax rate is beneficial to groups 2, 3, and 7 and detrimental to groups 1 and 6. The right-to-work laws induces growth of group 2 but intensify employment loss of group 7.

Demographic variables affect multiple groups but their directions are not identical across the corresponding groups. A higher percent of Black residents is mostly negative to growth and resilience. A higher percent of college or higher education on the other hand is mostly viewed as a positive factor to all three indices. A higher percent of foreign-born residents has mixed effects. It is beneficial to growth of group 6 and stabilization of group 2; detrimental to resilience of group 1; and has mixed impacts on groups 7 and 8 through conflicting indices.

A baseline unemployment rate affects the performance of most metropolitan areas in the next quarter century. A higher unemployment rate reduces growth, deepens employment loss, or limits resilience in most of the groups where this variable shows significance. The beginning economic condition thus seems to determine the future. The poverty rate has conflicting relationships across indices and groups and any pattern is hardly detected.

Next, the political stance leaning toward the Republican party leads groups 3, 6, and 7 grow or resilient without any adverse impact on the rest of the indices. However, if an MSA belongs to group 1 or 2, a higher percent of votes for a Republican candidate in the preceding presidential election intensifies its employment loss and slows down its speed of recovery, while it is a plus for the long-term growth. This mixed effect in better performing regions indicate that benefits an MSA receives due to its political stance become less important in maintaining its labor market strong and healthy as the metropolitan area's overall capabilities reach a high level.

Lastly, the sole variable that is significant in multiple groups and has an unchanging direction in all corresponding groups is the number of downturns an MSA experiences over the study period. This unchanging finding tells that processes of minimizing each crisis that a metropolitan area faces and recovering quickly from the minimized crisis is the key to minimize long-run employment losses and maximize its resilient power. In that, a prompt local response to a crisis is the answer.

	Group	1	Group	2	Group	3	Group	6	Group	7	Group	. 8
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Growth												
invcapt	8.45E-09	2.66E-08	2.12E-08	2.11E-08	3.53E-07***	1.33E-07	1.51E-09	1.18E-08	3.53E-09	8.86E-09	-1.77E-09	3.29E-09
ltdot	6.94E-07**	3.03E-07	4.07E-08	7.66E-08	-1.27E-07	1.91E-06	1.44E-06***	4.11E-07	2.28E-07	4.10E-07	-6.12E-08	2.16E-07
patent	11.4050***	4.3607	-4.1839†	2.7767	-8.9004	11.8158	-2.7787**	1.1369	1.3715	2.1518	0.2063	0.3031
cons	-0.0008†	0.0005	-0.0005	0.0007	0.0018***	0.0007	-0.0009***	0.0003	0.0003	0.0004	-0.0002	0.0004
manu	0.0001	0.0001	-0.0001	0.0002	-0.0002	0.0002	0.0002**	0.0001	4.65E-05	0.0001	-1.86E-05	4.49E-05
black	-0.0002**	0.0001	-4.87E-05	0.0001	-0.0001	0.0003	-2.95E-05	4.22E-05	-0.0001**	0.0001	-3.43E-05	0.0001
foreign	0.0001	0.0001	-7.21E-06	0.0002	-0.0004	0.0004	0.0002*	0.0001	0.0003**	0.0002	0.0001†	0.0001
coll	-0.0001	0.0001	-1.85E-05	0.0001	0.0001	0.0004	0.0002***	0.0001	0.0001	0.0001	-3.31E-05	0.0001
minwage	0.0004	0.0005	0.0003	0.0007	0.0010	0.0016	-0.0003	0.0005	-0.0012**	0.0006	-0.0022***	0.0008
emptax	-0.0033	0.0027	0.0041*	0.0023	0.0006	0.0046	-0.0019†	0.0013	0.0043**	0.0021	0.0016†	0.0012
right	-0.0018	0.0014	0.0032†	0.0024	-0.0037	0.0046	0.0006	0.0012	-0.0005	0.0016	-0.0001	0.0015
unemp	-0.0028***	0.0008	-0.0010	0.0009	0.0006	0.0009	0.0004	0.0003	-0.0012**	0.0006	0.0001	0.0004
pov	0.0006***	0.0002	0.0007**	0.0003	0.0013***	0.0004	-0.0001	0.0001	0.0006***	0.0002	-0.0003†	0.0002
repub	0.0001*	0.0001	0.0002**	0.0001	0.0002†	0.0002	0.0001***	4.44E-05	0.0001**	0.0001	-6.35E-06	0.000
instability	0.2462†	0.1851	0.0870	0.3075	-0.4557***	0.1270	-0.3870***	0.1113	-0.0528*	0.0285	-0.1317***	0.0237
resilience	0.0255	0.2141	0.8302†	0.5341	1.0096***	0.2204	-0.0277	0.1455	-0.1256**	0.0585	0.3823***	0.1473
_cons	0.0207	0.0164	-0.0086	0.0137	-0.0395†	0.0255	-0.0035	0.0062	-0.0051	0.0099	0.0142**	0.0071
Instability												
asset	-3.61E-09	9.44E-09	1.13E-09	7.12E-09	1.30E-07*	7.13E-08	-1.78E-08†	1.38E-08	2.10E-08	3.79E-08	-6.68E-09	7.19E-09
cst	1.41E-07	5.85E-07	-9.74E-07**	4.77E-07	-1.52E-06	1.80E-06	9.12E-07	9.55E-07	-1.88E-06	3.06E-06	9.90E-07	1.46E-06
herf	-0.0230	0.0629	0.0917	0.0931	-0.1782	0.1484	0.0094	0.0909	0.5377***	0.1358	0.1415	0.1449
gov	1.23E-05	0.0001	-0.0001	0.0001	0.0002	0.0003	-0.0003	0.0003	0.0015**	0.0007	-0.0002	0.0003
black	-0.0001	0.0001	1.22E-05	0.0001	-0.0003	0.0003	-0.0001	0.0001	-1.49E-05	0.0005	-0.0001	0.0003
foreign	0.0003*	0.0001	-0.0004***	0.0002	1.07E-05	0.0005	3.61E-05	0.0002	0.0014†	0.0009	0.0007†	0.0004
coll	-0.0001†	0.0001	-5.73E-06	0.0001	-0.0006**	0.0003	0.0002*	0.0001	-0.0002	0.0006	-0.0001	0.0003
minwage	-0.0006	0.0006	0.0001	0.0009	0.0005	0.0013	-0.0017**	0.0009	0.0052†	0.0038	-0.0147***	0.0044
emptax	0.0037†	0.0028	-7.30E-06	0.0026	-0.0054	0.0058	-0.0035	0.0031	-0.0042	0.0124	0.0097†	0.006
right	-0.0014	0.0016	0.0016	0.0027	-0.0033	0.0043	0.0004	0.0030	0.0164*	0.0092	-0.0016	0.007
unemp	0.0003	0.0010	0.0021**	0.0009	-0.0003	0.0012	-0.0001	0.0007	0.0083**	0.0035	0.0008	0.0022

Table 18. Three-Stage Least Squares Estimates by Median-Based Category

	Group	1	Group	2	Group	3	Group	6	Group	7	Group	8
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
pov	-0.0002	0.0003	-0.0002	0.0003	0.0011**	0.0006	-1.37E-05	0.0003	-0.0027*	0.0016	-0.0016**	0.0008
repub	0.0003***	0.0001	0.0002*	0.0001	-0.0001	0.0002	0.0001	0.0001	0.0003	0.0004	-0.0002	0.0004
span	-0.0014***	0.0003	-0.0009**	0.0003	-0.0006	0.0008	-0.0003	0.0003	-0.0035**	0.0015	-0.0010	0.0008
growth	-0.8887***	0.2981	-0.6465**	0.2825	-0.8101***	0.2279	-1.0636***	0.3776	-2.2821*	1.2480	-6.6548***	0.9355
resilience	0.6592***	0.1951	2.4558***	0.4578	1.6284***	0.1767	-0.2450	0.4511	0.6247†	0.3933	2.7283***	0.6847
_cons	0.0134	0.0121	-0.0356*	0.0182	0.0454**	0.0228	0.0252**	0.0127	-0.0662	0.0571	0.0835**	0.0419
Resilience												
stdot	-4.51E-06	1.09E-05	2.81E-06	3.25E-06	-1.58E-05	1.77E-05	-3.25E-07	1.33E-05	-3.83E-05	4.33E-05	6.22E-06	5.76E-06
tir	-4.35E-06	5.77E-06	-2.01E-07	1.45E-06	-1.88E-06	3.12E-06	-7.67E-06***	2.51E-06	-8.45E-06	1.45E-05	-2.14E-06	2.35E-06
self	-0.0004	0.0007	0.0001	0.0002	0.0004	0.0004	-0.0007	0.0006	-0.0010	0.0019	-0.0001	0.0003
black	0.0001	0.0002	2.22E-05	4.17E-05	0.0004*	0.0002	-1.48E-05	0.0001	-0.0007*	0.0004	0.0001	0.0001
foreign	-0.0004*	0.0002	0.0002**	0.0001	0.0001	0.0003	0.0001	0.0001	0.0021*	0.0013	-0.0002†	0.0001
coll	0.0002†	0.0002	3.14E-05	0.0001	0.0004***	0.0001	0.0001	0.0001	0.0004	0.0004	0.0001	0.0001
minwage	0.0014†	0.0010	-0.0001	0.0004	-0.0011†	0.0008	-0.0002	0.0009	-0.0076**	0.0032	0.0054***	0.0012
emptax	-0.0058†	0.0041	-0.0003	0.0013	0.0065**	0.0032	0.0014	0.0021	0.0266**	0.0125	-0.0029†	0.0022
right	0.0026	0.0024	-0.0009	0.0012	-0.0004	0.0022	0.0017	0.0017	-0.0027	0.0089	0.0012	0.0025
unemp	0.0003	0.0017	-0.0006†	0.0004	0.0003	0.0007	0.0022**	0.0009	-0.0063*	0.0033	-0.0001	0.0007
pov	0.0001	0.0004	-4.70E-07	0.0002	-0.0006**	0.0003	-0.0007*	0.0004	0.0026*	0.0013	0.0006*	0.0003
repub	-0.0005***	0.0002	-0.0001†	4.84E-05	2.75E-05	0.0001	0.0001	0.0001	0.0006†	0.0004	0.0001	0.0001
span	0.0023***	0.0007	0.0003†	0.0002	0.0007†	0.0004	0.0008**	0.0003	0.0004	0.0013	0.0002	0.0002
growth	1.4823***	0.4161	0.2998**	0.1460	0.5997***	0.1227	0.6475**	0.3171	-4.8223***	1.6893	2.1987***	0.4089
instability	1.6806***	0.5489	0.3344***	0.0983	0.5812***	0.0660	-0.1363	0.2177	-0.1962	0.2344	0.2808***	0.0634
_cons	-0.0204	0.0190	0.0107**	0.0049	-0.0270**	0.0119	0.0015	0.0097	0.0295	0.0500	-0.0339***	0.0113
n	4	5	5	51	2	9	3	6	2	4	6	51
R^2 (Grow.)	0.701	2	0.368	39	0.797	8	0.674	9	0.584	40	0.643	34
R^2 (Insta.)	0.263	0	-0.402	28	0.815	5	0.423	3	0.718	39	0.438	32
R^2 (Resil.)	0.222	4	0.233	38	0.879	6	0.421	4	-0.822	23	-0.006	59

Notes.

The coefficients and standard errors are rounded up to four significant figures. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test. † indicates statistical significance at the 90% level under the one-tailed test. Regressions of the 4th and 5th groups are omitted due to their small sample sizes.

The standardized coefficients depict variables with a stronger influence within a particular group (see Table 19). Notable strong regressors are the unemployment rate and poverty rate in mid-performing groups (groups 2, 3, 6 and 7). These variables tend to be among the strongest regressors in at least one of the three equations of the corresponding groups. These economic conditions at the onset of the study period are of smaller influence in the best and worst performing groups (groups 1 and 8). In addition to these variables, group 3 that grows fast, is unstable, and is resilience and group 6 that grows slowly, is stable, and is non-resilience are largely influenced by the utilization of public and private finance. For a policy perspective, noting that the financial variables rarely show statistical significance in other groups, the local governments' role of intervening their economy through the use of public funds becomes even more critical if a metropolitan area falls into the corresponding groups. Furthermore, extreme metropolitan areas, the best and worst performing areas, are likely to stay in the same categories over time and thus how to better shape an economic structure may be of interest more to nonextreme areas that move from a category to another relatively easily. In this sense, variables identified in this paragraph have a particular importance.

For the best performing group (group 1), the number of patents per employee is the greatest influence on their growth, and the political stance and the frequency of experiencing a downturn are of greater influences on instability and resilience. Lastly, the worst performing group (group 8) shows a close relationship with the minimum wage among all statistically significant regressors of the group. A higher minimum wage contributes to the short-term moves but adversely affects the long-term growth. Recalling that group 8 is classified so due to their relatively slow growth, instability, and non-resilience, the impact of minimum wage on

the short-term moves is not powerful enough to push them to a better performing group and its impact on the long-term growth is strong enough to put them into the group of slow growth.

	Group	1	Group	2	Group	3	Group	6	Group	7	Group	8
	Coef.	Beta	Coef.	Beta	Coef.	Beta	Coef.	Beta	Coef.	Beta	Coef.	Beta
Growth												
invcapt	8.45E-09	0.0446	2.12E-08	0.1120	3.53E-07***	1.8653	1.51E-09	0.0080	3.53E-09	0.0187	-1.77E-09	-0.0094
ltdot	6.94E-07**	0.3066	4.07E-08	0.0180	-1.27E-07	-0.0561	1.44E-06***	0.6359	2.28E-07	0.1007	-6.12E-08	-0.0270
patent	11.4050***	0.5607	-4.1839†	-0.2057	-8.9004	-0.4376	-2.7787**	-0.1366	1.3715	0.0674	0.2063	0.0101
cons	-0.0008†	-0.1408	-0.0005	-0.0963	0.0018***	0.3204	-0.0009***	-0.1658	0.0003	0.0541	-0.0002	-0.0279
manu	0.0001	0.0459	-0.0001	-0.0569	-0.0002	-0.1535	0.0002**	0.2122	4.65E-05	0.0422	-1.86E-05	-0.0169
black	-0.0002**	-0.2160	-4.87E-05	-0.0547	-0.0001	-0.0866	-2.95E-05	-0.0331	-0.0001**	-0.1607	-3.43E-05	-0.0385
foreign	0.0001	0.0320	-7.21E-06	-0.0040	-0.0004	-0.2292	0.0002*	0.0947	0.0003**	0.1782	0.0001†	0.0655
coll	-0.0001	-0.0751	-1.85E-05	-0.0186	0.0001	0.0660	0.0002***	0.2242	0.0001	0.0855	-3.31E-05	-0.0334
minwage	0.0004	0.0623	0.0003	0.0490	0.0010	0.1642	-0.0003	-0.0414	-0.0012**	-0.1910	-0.0022***	-0.3565
emptax	-0.0033	-0.1290	0.0041*	0.1603	0.0006	0.0234	-0.0019†	-0.0755	0.0043**	0.1687	0.0016†	0.0625
right	-0.0018	-0.1023	0.0032†	0.1778	-0.0037	-0.2092	0.0006	0.0319	-0.0005	-0.0260	-0.0001	-0.0071
unemp	-0.0028***	-0.5417	-0.0010	-0.1962	0.0006	0.1166	0.0004	0.0694	-0.0012**	-0.2193	0.0001	0.0180
pov	0.0006***	0.3374	0.0007**	0.3587	0.0013***	0.6959	-0.0001	-0.0459	0.0006***	0.3251	-0.0003†	-0.1345
repub	0.0001*	0.1473	0.0002**	0.1587	0.0002†	0.2306	0.0001***	0.1487	0.0001**	0.1526	-6.35E-06	-0.0065
instability	0.2462†	0.6325	0.0870	0.2234	-0.4557***	-1.1707	-0.3870***	-0.9942	-0.0528*	-0.1357	-0.1317***	-0.3383
resilience	0.0255	0.0304	0.8302†	0.9880	1.0096***	1.2015	-0.0277	-0.0329	-0.1256**	-0.1494	0.3823***	0.4550
_cons	0.0207	1.3093	-0.0086	1.1002	-0.0395†	0.7608	-0.0035	-0.8050	-0.0051	-0.3748	0.0142**	-0.3832
Instability	_											
asset	-3.61E-09	-0.0163	1.13E-09	0.0051	1.30E-07*	0.5883	-1.78E-08†	-0.0804	2.10E-08	0.0951	-6.68E-09	-0.0302
cst	1.41E-07	0.0065	-9.74E-07**	-0.0447	-1.52E-06	-0.0699	9.12E-07	0.0418	-1.88E-06	-0.0861	9.90E-07	0.0454
herf	-0.0230	-0.0153	0.0917	0.0608	-0.1782	-0.1181	0.0094	0.0062	0.5377***	0.3566	0.1415	0.0938
gov	1.23E-05	0.0031	-0.0001	-0.0247	0.0002	0.0597	-0.0003	-0.0733	0.0015**	0.3766	-0.0002	-0.0601
black	-0.0001	-0.0395	1.22E-05	0.0053	-0.0003	-0.1332	-0.0001	-0.0363	-1.49E-05	-0.0065	-0.0001	-0.0540
foreign	0.0003*	0.0589	-0.0004***	-0.0945	1.07E-05	0.0023	3.61E-05	0.0077	0.0014†	0.3098	0.0007†	0.1531
coll	-0.0001†	-0.0572	-5.73E-06	-0.0023	-0.0006**	-0.2179	0.0002*	0.0936	-0.0002	-0.0867	-0.0001	-0.0568
minwage	-0.0006	-0.0390	0.0001	0.0093	0.0005	0.0342	-0.0017**	-0.1057	0.0052†	0.3221	-0.0147***	-0.9171
emptax	0.0037†	0.0560	-7.30E-06	-0.0001	-0.0054	-0.0825	-0.0035	-0.0541	-0.0042	-0.0644	0.0097†	0.1493
right	-0.0014	-0.0316	0.0016	0.0345	-0.0033	-0.0728	0.0004	0.0081	0.0164*	0.3594	-0.0016	-0.0341
unemp	0.0003	0.0240	0.0021**	0.1579	-0.0003	-0.0216	-0.0001	-0.0089	0.0083**	0.6183	0.0008	0.0564

 Table 19. Three-Stage Least Squares Beta Coefficients by Median-Based Category

	Group	1	Group	2	Group	3	Group	6	Group	7	Group	8
	Coef.	Beta	Coef.	Beta	Coef.	Beta	Coef.	Beta	Coef.	Beta	Coef.	Beta
pov	-0.0002	-0.0341	-0.0002	-0.0384	0.0011**	0.2297	-1.37E-05	-0.0028	-0.0027*	-0.5664	-0.0016**	-0.3416
repub	0.0003***	0.1222	0.0002*	0.0653	-0.0001	-0.0237	0.0001	0.0368	0.0003	0.1382	-0.0002	-0.0640
span	-0.0014***	-0.1848	-0.0009**	-0.1193	-0.0006	-0.0774	-0.0003	-0.0451	-0.0035**	-0.4659	-0.0010	-0.1299
growth	-0.8887***	-0.3459	-0.6465**	-0.2516	-0.8101***	-0.3153	-1.0636***	-0.4140	-2.2821*	-0.8883	-6.6548***	-2.5903
resilience	0.6592***	0.3054	2.4558***	1.1376	1.6284***	0.7543	-0.2450	-0.1135	0.6247†	0.2894	2.7283***	1.2638
_cons	0.0134	-0.4013	-0.0356*	0.0326	0.0454**	0.3819	0.0252**	-0.7148	-0.0662	-0.2412	0.0835**	-0.9383
Resilience												
stdot	-4.51E-06	-0.0318	2.81E-06	0.0198	-1.58E-05	-0.1113	-3.25E-07	-0.0023	-3.83E-05	-0.2698	6.22E-06	0.0438
tir	-4.35E-06	-0.1036	-2.01E-07	-0.0048	-1.88E-06	-0.0447	-7.67E-06***	-0.1826	-8.45E-06	-0.2011	-2.14E-06	-0.0509
self	-0.0004	-0.0725	0.0001	0.0212	0.0004	0.0574	-0.0007	-0.1076	-0.0010	-0.1563	-0.0001	-0.0161
black	0.0001	0.1321	2.22E-05	0.0209	0.0004*	0.3670	-1.48E-05	-0.0140	-0.0007*	-0.6635	0.0001	0.0918
foreign	-0.0004*	-0.1929	0.0002**	0.0850	0.0001	0.0654	0.0001	0.0371	0.0021*	0.9883	-0.0002†	-0.0919
coll	0.0002†	0.2081	3.14E-05	0.0267	0.0004***	0.3233	0.0001	0.0610	0.0004	0.3337	0.0001	0.0471
minwage	0.0014†	0.1861	-0.0001	-0.0184	-0.0011†	-0.1427	-0.0002	-0.0244	-0.0076**	-1.0179	0.0054***	0.7306
emptax	-0.0058†	-0.1916	-0.0003	-0.0089	0.0065**	0.2163	0.0014	0.0448	0.0266**	0.8795	-0.0029†	-0.0957
right	0.0026	0.1221	-0.0009	-0.0412	-0.0004	-0.0190	0.0017	0.0808	-0.0027	-0.1287	0.0012	0.0573
unemp	0.0003	0.0500	-0.0006†	-0.0959	0.0003	0.0460	0.0022**	0.3579	-0.0063*	-1.0027	-0.0001	-0.0153
pov	0.0001	0.0388	-4.70E-07	-0.0002	-0.0006**	-0.2782	-0.0007*	-0.3245	0.0026*	1.1630	0.0006*	0.2716
repub	-0.0005***	-0.4329	-0.0001†	-0.0589	2.75E-05	0.0236	0.0001	0.0688	0.0006†	0.5173	0.0001	0.0955
span	0.0023***	0.6771	0.0003†	0.0798	0.0007†	0.1972	0.0008**	0.2210	0.0004	0.1217	0.0002	0.0479
growth	1.4823***	1.2456	0.2998**	0.2519	0.5997***	0.5039	0.6475**	0.5441	-4.8223***	-4.0520	2.1987***	1.8475
instability	1.6806***	3.6280	0.3344***	0.7219	0.5812***	1.2546	-0.1363	-0.2942	-0.1962	-0.4236	0.2808***	0.6063
_cons	-0.0204	1.4098	0.0107**	-0.1313	-0.0270**	-0.2618	0.0015	-0.7279	0.0295	-1.3051	-0.0339***	0.5996
n	45		5	1	29)	30	5	4	4	6	1
R^2 (Grow.)	0.7012		0.3689)	0.7978	3	0.6749	•	0.584	0	0.6434	4
R^2 (Insta.)	0.2630	1	-0.402	8	0.8155	5	0.4233	3	0.718	9	0.4382	2
R^2 (Resil.)	0.2224		0.2338	3	0.8796	5	0.4214	4	-0.822	3	-0.0069	9

Notes.

The coefficients and standard errors are rounded up to four significant figures. *, **, and *** indicate statistical significance at the 90%, 95%, and 99% levels respectively under the two-tailed test. † indicates statistical significance at the 90% level under the one-tailed test. Regressions of the 4th and 5th groups are omitted due to their small sample sizes.

CHAPTER 4. CONCLUSION

1. Summary

All metropolitan areas included in this study are officially called MSAs as their populations have met a certain threshold. This threshold distinguishes MSAs from the rest of the nation. This study however has confirmed that employment dynamics differ greatly within this group of areas. By applying two new measures for instability and resilience, in addition to using the traditional long-term growth rate, this study has captured short-term movements of metropolitan economy that were veiled under long-term growth rates. Even if two metropolitan areas have shown similar growth rates over the past quarter century, one has grown steadily while another has gone through frequent ups and downs. A wide range of differences exists in their ability to maintain employment against shocks and their speed of return to previous peak employment after a downturn.

A meaningful aspect of this study is that dynamics of "sub-national" geographic entities have been examined apart from national recessionary periods. The instability and resilience measures have reflected local shocks that likely happen regardless of national trends. Furthermore, this study intentionally has not distinguished reasons for shocks for an increased generalizability. Any type of shock may happen to a metropolitan area, the area's preparation should be made for all shocks from natural disasters to the collapse of a major corporation or to the mass departure of workers to a nearby bustling metropolitan area. Measures suggested this way therefore have increased generalizability and applicability. Through statistical analyses, this study identifies socioeconomic, political, and policy variables that determine the level of growth, instability, and resilience of metropolitan areas. Some of the variables in particular show statistical significance across sub-periods, Census Regions, and scales of economy. Such variables may relate to possible nationwide policies for stabilizing regional employment. Those that show statistical significance in part of the nation may on the other hand be useful for local governments to establish their own local policies specific to their locales. Findings from Sections 3 and 4 of Chapter 3 may contribute to their policy making.

In addition to the explanatory factors that relate to each of the measures, the analysis has revealed a trend. The number of significant variables explaining resilience is certainly less than that for growth or instability. R^2 of resilience models have been lower than those of the other two models in general. This tendency implies that resilience is less dependent on a widely tested set of socioeconomic quantifiable factors than growth and instability.

2. Policy Implications

This study looks at employment dynamics from three angles simultaneously, and factors positively or negatively affecting regional economies from all angles has been limited to a few. This simultaneous analysis, paired with categorical analyses, leaves out false positives, ensuring the meanings of select factors. Such factors are what governmental policies may utilize at first and select variables are restated here.

The most straightforward finding is that a lower unemployment rate within a metropolitan area contributes to faster growth, a more stable employment, or a faster recovery of the area. The past economic condition determines the present, and the present

determines the future path. To ensure growth, instability, and resilience in the future, a metropolitan area must maintain its present unemployment rate low enough.

A higher state average employer tax rate also shows a positive impact on metropolitan employment dynamics. A more active intervention of state governments to establish an enough safety net for the unemployed in deed results in a growing, stable, and resilient labor market. Note that this variable relates to the unemployed as the first variable does. This outcome indicates that it is these people to whom the governments should pay attention and that it is these people that determine the overall health of the labor market.

Next consistent factor is the poverty rate of metropolitan areas. A higher poverty rate is found to be associated with faster growth, a more stable employment, or a faster recovery. Considering that the unemployed tend to be impoverished and vice versa, this finding might raise a question to some readers of whether a metropolitan area should aim at a higher poverty rate or at least ignore poverty for the whole economy. The answer is of course, no. Unlike the unemployment rate and the employer tax rate, this factor needs an indirect interpretation. The proper interpretation is that the impoverished are not an obstacle but could signal the potential for a healthier economy. It may be due to the firmer willingness of such disadvantaged people to work under adverse condition. Therefore, in relation to the unemployed, policies should aim at securing jobs for this group of workers.

A higher percent of college or higher education is found to be associated with a healthy economy in general. Higher education has frequently appeared in literature as an influencing factor for growth or resilience. One may assume that higher or lower education of workers are associated with certain industries and that the proportion of those industries is more critical. Still, considering that none of the shares of select industries do not show a consistent meaningful impact, it is truly education itself that may lead the economy to a healthy growth path. Skilled workers may contribute to the wellbeing of firms, which in turn brings a growing, stable, and resilient labor market to the area.

Race represented as the percent of Black residents is another influencing factor. A healthier path is linked to a lower percent of Black residents. This demographic factor is not something that a policy may change. Rather, it opens up a space for governments to intervene and cut the negative relationship between this factor and the economy. The relationship with the percent of Black residents and other socioeconomic variables clearly should be examined further. If the unemployment rate of this group is higher than that of the rest of the area's population or the educational attainment of this group is lower than that of the rest of the population, the findings become comprehensible and the policy directions become clear. Policies to foster employment and promote educational attainment, leading to a desirable growth path.

3. Limitations and Future Research

First of all, the series of regression analysis that I performed confirms that quantifiable factors, which have appeared in theories and empirical research elsewhere, explain less of the resilience equation than those for growth or instability. This persistent tendency demonstrates that the short-term upward move may associate with as yet unknown, or at least latent, quantitative factors or non-quantifiable practices of metropolitan areas that enable the return to the pre-downturn employment levels. Considering that the list of right-hand-side variables in this study is fairly comprehensive, it seems that any important remaining unknown factors are likely to be qualitative. Therefore, a qualitative case study of select metropolitan areas could be expected to explain remaining puzzles of the resilience equation. In addition to practices of local governments, firms, and non-profit organizations to combat employment loss, perceptions/opinions of residents on social, economic, and political issues are an interesting aspect to examine given that the political stance of residents appears related to the employment dynamics in this study. The examination of historical incidences of political and social unrest seemingly focused on particular issues could be clues to residents' perceptions.

This study may also be expanded through further quantitative approaches. The only variable that has appeared in the theoretical literature but not included in the in the righthand-side variable list is intertemporal elasticity of substitution. Due to the lack of publicly available individual level financial data, such information was omitted from this study. If the access to the Survey of Consumer Finance at the individual or even metropolitan level is granted, the independent variable list could become more complete. More broadly, supranational structural changes, such as the burgeoning robotics industry and more diversified national global value chains, could also impact metropolitan employment dynamics. In this vein, controlling for grand external forces such as industry change, immigration, and international trade could be incorporated to enhance the models used here, which currently ignore such global trends (are closed). The application of Bartik's instrument (Bartik, 1991; Blanchard & Katz, 1992; Baum-Snow & Ferreira, 2015) to the analysis could help explorations into relationships between the national industrial dynamics and the regional employment dynamics, which likewise could reflect supranational structural changes.

In addition, this study is based on employment counts but other economic variables may be examined instead. Gross metropolitan product, an average wage of workers, the productivity of labor, and the productivity of capital are possible dependent variables to be used in addition to employment counts. The use of these extra variables could help metropolitan economies attack their decline from different angles and lead to a deeper understanding of the nature of their economies.

The current analysis intentionally ignores different types of shocks as the focus is to increase the metropolitan areas' preparedness to *any* shock. A more effective method of maintaining stable employment against a shock and recovering promptly after the shock could vary by the source of shocks. National recessions, natural disasters, and terrors, for example, could require different types of local efforts for stabilization and recovery. Future research may explore such possibilities by differentiating sources of shocks.

Next, there is a room for further improvement of the model structure. Due to the nature of how the three indices – growth, instability, and resilience measures – are defined, the right-hand-side variables at the starting year of a given period are used in the analysis despite the availability of longitudinal data. If the current model is further developed so that longitudinal data can be employed, it could enable the use of more information and, hence, capture some of the more delicate relationships among variables, increasing the model's predictability. Such a forecast model could add much to the literature. The ultimate purpose of studies in the context of labor market dynamics is to prepare metropolitan areas for downturns. While this study suggests a set of conditions and policies that metropolitan areas could implement to position themselves in a more secure and healthier path, it informs the present only based on past metropolitan economic behavior. The future is

beyond the scope of this study. If a viable forecast model can be devised that could inform

metropolitan areas of their future trajectory, their preparation could be better informed and

directed, given a specific time and/or employment level.

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APPENDIX A

Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
Atlanta-Sandy Springs-Roswell, GA	0.0190 (63)	0.0166 (162)	0.0223 (156)	3	1	3
Auburn-Opelika, AL	0.0202 (57)	0.0117 (105)	0.0295 (68)	12	1	3
Austin-Round Rock, TX	0.0350 (5)	0.0069 (46)	0.0306 (57)	3	1	1
Bakersfield, CA	0.0168 (80)	0.0110 (96)	0.0246 (124)	15	1	1
Billings, MT	0.0184 (66)	0.0042 (20)	0.0235 (140)	15	1	1
Boise City, ID	0.0292 (14)	0.0194 (190)	0.0251 (115)	4	1	3
Bremerton-Silverdale, WA	0.0116 (178)	0.0128 (122)	0.0204 (190)	11	1	3
Brownsville-Harlingen, TX	0.0223 (39)	0.0025 (10)	0.0231 (148)	10	1	1
Casper, WY	0.0124 (167)	0.0173 (168)	0.0347 (38)	16	1	3
Charlotte-Concord-Gastonia, NC-SC	0.0188 (65)	0.0136 (134)	0.0246 (123)	4	1	3
Chico, CA	0.0113 (187)	0.0189 (186)	0.0233 (147)	9	1	3
Clarksville, TN-KY	0.0203 (55)	0.0084 (64)	0.0262 (96)	11	1	1
College Station-Bryan, TX	0.0218 (41)	0.0031 (16)	0.0261 (100)	11	1	1
Columbia, MO	0.0181 (69)	0.0026 (11)	0.0308 (56)	13	1	1
Columbia, SC	0.0129 (159)	0.0130 (124)	0.0221 (159)	10	1	3
Dallas-Fort Worth-Arlington, TX	0.0209 (48)	0.0102 (82)	0.0221 (160)	3	1	1
Daphne-Fairhope-Foley, AL	0.0367 (3)	0.0126 (120)	0.0255 (111)	7	1	3
Denver-Aurora-Lakewood, CO	0.0206 (50)	0.0110 (97)	0.0229 (152)	4	1	1
Des Moines-West Des Moines, IA	0.0161 (92)	0.0042 (19)	0.0275 (85)	11	1	1
Dover, DE	0.0182 (68)	0.0108 (93)	0.0339 (43)	13	1	1
Elizabethtown-Fort Knox, KY	0.0152 (112)	0.0063 (36)	0.0313 (52)	15	1	1
Fairbanks, AK	0.0117 (177)	0.0072 (49)	0.0277 (82)	15	1	1
Fayetteville, NC	0.0119 (173)	0.0102 (83)	0.0309 (54)	8	1	1
Fort Collins, CO	0.0281 (15)	0.0051 (30)	0.0255 (112)	4	1	1
Fresno, CA	0.0115 (182)	0.0136 (133)	0.0209 (179)	13	1	3
Gainesville, GA	0.0257 (20)	0.0167 (165)	0.0301 (61)	12	1	3
Greeley, CO	0.0307 (11)	0.0083 (63)	0.0582 (11)	10	1	1
Hagerstown-Martinsburg, MD-WV	0.0133 (150)	0.0073 (51)	0.0239 (133)	14	1	1
Hattiesburg, MS	0.0153 (109)	0.0123 (115)	0.0235 (143)	12	1	3
Hinesville, GA	0.0226 (37)	0.0103 (85)	0.0439 (20)	12	1	1
Huntsville, AL	0.0130 (157)	0.0084 (65)	0.0220 (164)	10	1	1
Idaho Falls, ID	0.0200 (58)	0.0165 (160)	0.0418 (23)	9	1	3
Iowa City, IA	0.0205 (51)	0.0017 (6)	0.0418 (23)	18	1	1
Jacksonville, FL	0.0170 (78)	0.0190 (187)	0.0238 (134)	7	1	3
Jacksonville, NC	0.0168 (82)	0.0065 (40)	0.0233 (134)	7	1	1
Jonesboro, AR	0.0159 (99)	0.0052 (31)	0.0209 (182)	8	1	1
Killeen-Temple, TX	0.0228 (36)	0.0019 (7)	0.0207 (162)	15	1	1
Lafayette, LA	0.0126 (161)	0.0173 (171)	0.0227 (101)	9	1	3
Larayette, LA Lake Charles, LA	0.0120 (101)		0.0237 (137)	9	1	3
		0.0186 (183)				
Laredo, TX	0.0322 (9)	0.0058 (34) 0.0029 (15)	0.0304 (59) 0.0291 (72)	11	1	1
Las Cruces, NM Logan, UT-ID	0.0183 (67) 0.0245 (27)	0.0029 (15) 0.0063 (37)	0.0291 (72)	16 10	1	1
•		0.0063 (37)	· · · · ·			1
Longview, TX	0.0126 (162)	× ,	0.0319 (49)	11	1	3
Lubbock, TX	0.0137 (140)	0.0044 (22)	0.0260 (101)	15	1	1
Madera, CA	0.0231 (35)	0.0178 (175)	0.0517 (13)	15	1	3
Merced, CA	0.0130 (155)	0.0070 (47)	0.0249 (117)	11	1	1
Miami-Fort Lauderdale-West Palm Beach, FL	0.0138 (137)	0.0173 (172)	0.0224 (155)	7	1	3
Morgantown, WV	0.0173 (77)	0.0071 (48)	0.0245 (125)	10	1	1
Napa, CA	0.0203 (54)	0.0128 (123)	0.0239 (131)	10	1	3

Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
Nashville-DavidsonMurfreesboroFranklin, TN	0.0207 (49)	0.0085 (67)	0.0212 (176)	7	1	1
Oklahoma City, OK	0.0129 (158)	0.0064 (38)	0.0208 (183)	9	1	1
Olympia-Tumwater, WA	0.0216 (45)	0.0089 (76)	0.0209 (181)	7	1	1
Orlando-Kissimmee-Sanford, FL	0.0254 (21)	0.0147 (146)	0.0315 (51)	8	1	3
Portland-Vancouver-Hillsboro, OR-WA	0.0181 (70)	0.0141 (140)	0.0236 (139)	3	1	3
Provo-Orem, UT	0.0338 (7)	0.0130 (126)	0.0339 (42)	4	1	3
Raleigh, NC	0.0279 (16)	0.0088 (75)	0.0273 (87)	3	1	1
Salem, OR	0.0164 (90)	0.0148 (151)	0.0239 (132)	9	1	3
Salt Lake City, UT	0.0232 (34)	0.0108 (94)	0.0222 (158)	3	1	1
San Luis Obispo-Paso Robles-Arroyo Grande, CA	0.0161 (93)	0.0118 (107)	0.0329 (45)	12	1	3
Savannah, GA	0.0160 (95)	0.0130 (125)	0.0235 (142)	9	1	3
Seattle-Tacoma-Bellevue, WA	0.0161 (94)	0.0145 (143)	0.0249 (118)	5	1	3
The Villages, FL	0.0569 (1)	0.0169 (167)	0.1046 (2)	14	1	3
Victoria, TX	0.0125 (164)	0.0168 (166)	0.0269 (91)	9	1	3
Visalia-Porterville, CA	0.0140 (133)	0.0156 (155)	0.0485 (16)	15	1	3
Waco, TX	0.0140 (131)	0.0072 (50)	0.0208 (184)	12	1	1
Warner Robins, GA	0.0149 (116)	0.0082 (62)	0.0214 (171)	13	1	1
Wenatchee, WA	0.0152 (111)	0.0157 (156)	0.0263 (95)	11	1	3
Winchester, VA-WV	0.0174 (75)	0.0134 (129)	0.0299 (63)	10	1	3
		. ,		Count		68
Amarillo, TX	0.0140 (132)	0.0049 (26)	0.0108 (356)	10	2	2
Ames, IA	0.0139 (136)	0.0065 (39)	0.0163 (263)	11	2	1
Anchorage, AK	0.0150 (114)	0.0014 (5)	0.0120 (336)	13	2	2
Appleton, WI	0.0139 (135)	0.0125 (119)	0.0187 (218)	9	2	3
Asheville, NC	0.0136 (143)	0.0125 (117)	0.0133 (318)	9	2	4
Athens-Clarke County, GA	0.0142 (128)	0.0173 (169)	0.0154 (279)	6	2	3
Barnstable Town, MA	0.0113 (188)	0.0145 (144)	0.0174 (236)	9	2	3
Baton Rouge, LA	0.0155 (105)	0.0080 (59)	0.0144 (295)	10	2	2
Bellingham, WA	0.0205 (52)	0.0109 (95)	0.0165 (256)	7	2	1
Bismarck, ND	0.0226 (38)	0.0008 (2)	0.0162 (266)	8	2	1
Bowling Green, KY	0.0191 (61)	0.0088 (74)	0.0184 (223)	15	2	1
California-Lexington Park, MD	0.0246 (26)	0.0009 (4)	0.0140 (306)	11	2	2
Cedar Rapids, IA	0.0118 (175)	0.0114 (101)	0.0166 (255)	15	2	3
Charleston-North Charleston, SC	0.0190 (64)	0.0086 (69)	0.0194 (206)	8	2	1
Charlottesville, VA	0.0148 (119)	0.0081 (60)	0.0163 (265)	7	2	1
Cheyenne, WY	0.0154 (107)	0.0049 (25)	0.0189 (216)	9	2	1
Colorado Springs, CO	0.0216 (44)	0.0139 (135)	0.0162 (268)	4	2	3
Columbus, OH	0.0132 (151)	0.0076 (55)	0.0147 (292)	4	2	1
Corpus Christi, TX	0.0130 (154)	0.0068 (44)	0.0171 (241)	10	2	1
Durham-Chapel Hill, NC	0.0165 (88)	0.0093 (79)	0.0198 (201)	7	2	1
Eau Claire, WI	0.0135 (145)	0.0147 (147)	0.0153 (282)	6	2	3
El Paso, TX	0.0141 (130)	0.0025 (9)	0.0123 (333)	10	2	2
Fargo, ND-MN	0.0242 (30)	0.0009 (3)	0.0123 (333)	8	2	2
Fayetteville-Springdale-Rogers, AR-MO	0.0301 (13)	0.0050 (28)	0.0170 (243)	6	2	1
Flagstaff, AZ	0.0167 (85)	0.0155 (154)	0.0170 (245)	7	2	3
Grand Forks, ND-MN	0.0113 (186)	0.0028 (14)	0.0126 (330)	15	2	2
Grand Island, NE	0.0137 (138)	0.0051 (29)	0.0120 (330)	10	2	1
Green Bay, WI	0.0159 (96)	0.0087 (73)	0.0104 (25)	6	2	2
Greenville, NC	0.0159 (90)	0.0087 (73)	0.0101 (301)	8	2	3
Hammond, LA	0.0137 (102)	0.0130 (132)	0.0138 (273)	7	2	4
Hammond, LA Harrisonburg, VA	0.0232 (23)	0.0123 (118)	0.0103 (339)		2	4
namsonourg, vA	0.0108 (84)	0.0077 (37)	0.0138 (274)	11	2	1

Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
Hot Springs, AR	0.0115 (183)	0.0148 (148)	0.0133 (319)	12	2	4
Houston-The Woodlands-Sugar Land, TX	0.0203 (56)	0.0045 (23)	0.0202 (195)	6	2	1
Indianapolis-Carmel-Anderson, IN	0.0124 (166)	0.0085 (66)	0.0162 (267)	10	2	1
Kennewick-Richland, WA	0.0218 (42)	0.0067 (42)	0.0195 (204)	6	2	1
Knoxville, TN	0.0129 (160)	0.0121 (113)	0.0139 (307)	8	2	4
La Crosse-Onalaska, WI-MN	0.0115 (181)	0.0046 (24)	0.0127 (328)	10	2	2
Lawrence, KS	0.0156 (103)	0.0121 (114)	0.0142 (300)	10	2	4
Lewiston, ID-WA	0.0120 (172)	0.0112 (99)	0.0179 (231)	13	2	1
Lexington-Fayette, KY	0.0145 (126)	0.0113 (100)	0.0172 (239)	5	2	1
Lincoln, NE	0.0145 (123)	0.0037 (17)	0.0127 (329)	6	2	2
Madison, WI	0.0156 (104)	0.0041 (18)	0.0177 (233)	5	2	1
Manhattan, KS	0.0153 (110)	0.0087 (71)	0.0143 (298)	9	2	2
Mankato-North Mankato, MN	0.0168 (83)	0.0074 (52)	0.0183 (227)	13	2	1
McAllen-Edinburg-Mission, TX	0.0321 (10)	0.0008 (1)	0.0184 (224)	9	2	1
Minneapolis-St. Paul-Bloomington, MN-WI	0.0121 (171)	0.0103 (84)	0.0173 (237)	5	2	1
Missoula, MT	0.0222 (40)	0.0043 (21)	0.0170 (242)	17	2	1
Mount Vernon-Anacortes, WA	0.0190 (62)	0.0167 (164)	0.0174 (235)	6	2	3
Ogden-Clearfield, UT	0.0215 (46)	0.0087 (72)	0.0170 (245)	8	2	1
Omaha-Council Bluffs, NE-IA	0.0131 (152)	0.0067 (41)	0.0152 (284)	8	2	1
Oshkosh-Neenah, WI	0.0113 (185)	0.0135 (130)	0.0136 (314)	7	2	4
Panama City, FL	0.0150 (115)	0.0121 (112)	0.0141 (302)	8	2	4
Pueblo, CO	0.0133 (148)	0.0105 (89)	0.0167 (250)	6	2	1
Rapid City, SD	0.0165 (89)	0.0027 (13)	0.0133 (317)	12	2	2
Rochester, MN	0.0148 (120)	0.0063 (35)	0.0182 (228)	14	2	1
Salisbury, MD-DE	0.0134 (147)	0.0143 (141)	0.0163 (262)	9	2	3
San Antonio-New Braunfels, TX	0.0235 (31)	0.0022 (8)	0.0127 (327)	6	2	2
San Diego-Carlsbad, CA	0.0133 (149)	0.0166 (161)	0.0199 (198)	8	2	3
Sioux Falls, SD	0.0244 (29)	0.0026 (12)	0.0167 (252)	7	2	1
Spokane-Spokane Valley, WA	0.0153 (108)	0.0148 (150)	0.0129 (325)	7	2	4
Springfield, MO	0.0168 (81)	0.0125 (116)	0.0200 (197)	9	2	3
St. Cloud, MN	0.0173 (76)	0.0075 (53)	0.0179 (229)	9	2	1
Tuscaloosa, AL	0.0137 (142)	0.0105 (90)	0.0150 (289)	7	2	1
Tyler, TX	0.0179 (71)	0.0056 (33)	0.0154 (280)	12	2	1
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.0114 (184)	0.0050 (27)	0.0120 (341)	5	2	2
Yakima, WA	0.0131 (153)	0.0079 (58)	0.0144 (294)	15	2	1
				Count		66
Albany, OR	0.0118 (174)	0.0312 (281)	0.0235 (141)	4	3	3
Bend-Redmond, OR	0.0346 (6)	0.0341 (296)	0.0366 (35)	7	3	3
Boulder, CO	0.0162 (91)	0.0928 (374)	0.0668 (9)	4	3	3
Cape Coral-Fort Myers, FL	0.0269 (18)	0.0326 (290)	0.0376 (31)	9	3	3
Carson City, NV	0.0121 (170)	0.0498 (340)	0.0399 (25)	8	3	3
Coeur d'Alene, ID	0.0333 (8)	0.0252 (240)	0.0385 (29)	6	3	3
Columbus, IN	0.0157 (100)	0.0329 (291)	0.0215 (169)	7	3	3
Crestview-Fort Walton Beach-Destin, FL	0.0212 (47)	0.0247 (235)	0.0340 (40)	10	3	3
Deltona-Daytona Beach-Ormond Beach, FL	0.0149 (118)	0.0262 (250)	0.0282 (81)	11	3	3
El Centro, CA	0.0130 (156)	0.0232 (221)	0.0368 (34)	13	3	3
Eugene, OR	0.0112 (189)	0.0308 (277)	0.0204 (191)	4	3	3
Farmington, NM	0.0159 (97)	0.0258 (246)	0.0308 (55)	8	3	3
Gainesville, FL	0.0125 (165)	0.0259 (247)	0.0243 (129)	9	3	3
Grand Junction, CO	0.0218 (43)	0.0378 (309)	0.0214 (172)	7	3	3
Grand Rapids-Wyoming, MI	0.0149 (117)	0.0357 (304)	0.0298 (65)	6	3	3
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Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
Grants Pass, OR	0.0139 (134)	0.0338 (294)	0.0262 (98)	8	3	3
Hanford-Corcoran, CA	0.0157 (101)	0.0284 (264)	0.0493 (14)	12	3	3
Hilton Head Island-Bluffton-Beaufort, SC	0.0253 (22)	0.0261 (249)	0.0233 (145)	6	3	3
Homosassa Springs, FL	0.0143 (127)	0.0290 (265)	0.0260 (104)	11	3	3
Houma-Thibodaux, LA	0.0151 (113)	0.0239 (226)	0.0369 (32)	10	3	3
Kahului-Wailuku-Lahaina, HI	0.0159 (98)	0.0228 (217)	0.0230 (150)	8	3	3
Lake Havasu City-Kingman, AZ	0.0234 (32)	0.0715 (360)	0.0694 (6)	9	3	3
Lakeland-Winter Haven, FL	0.0111 (190)	0.0277 (262)	0.0230 (149)	11	3	3
Las Vegas-Henderson-Paradise, NV	0.0364 (4)	0.0324 (288)	0.0296 (66)	3	3	3
Midland, TX	0.0250 (24)	0.0294 (267)	0.0357 (36)	5	3	3
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	0.0264 (19)	0.0221 (211)	0.0748 (4)	5	3	3
Naples-Immokalee-Marco Island, FL	0.0274 (17)	0.0431 (322)	0.0425 (21)	9	3	3
North Port-Sarasota-Bradenton, FL	0.0155 (106)	0.0491 (339)	0.0388 (26)	13	3	3
Ocala, FL	0.0175 (74)	0.0434 (324)	0.0258 (108)	8	3	3
Odessa, TX	0.0166 (87)	0.0302 (273)	0.0298 (64)	10	3	3
Phoenix-Mesa-Scottsdale, AZ	0.0248 (25)	0.0247 (234)	0.0213 (174)	4	3	3
Pocatello, ID	0.0167 (86)	0.0399 (312)	0.0289 (74)	6	3	3
Port St. Lucie, FL	0.0191 (60)	0.0259 (248)	0.0306 (58)	10	3	3
Prescott, AZ	0.0303 (12)	0.0479 (336)	0.0423 (22)	7	3	3
Punta Gorda, FL	0.0204 (53)	0.1358 (381)	0.0684 (7)	7	3	3
Reno, NV	0.0170 (79)	0.0426 (319)	0.0259 (107)	6	3	3
Riverside-San Bernardino-Ontario, CA	0.0245 (28)	0.0420 (313)	0.0239 (107)	7	3	3
SacramentoRosevilleArden-Arcade, CA	. ,			6	3	3
	0.0146 (122)	0.0227 (216)	0.0239 (130)		3	
Santa Rosa, CA Sebastian-Vero Beach, FL	0.0125 (163)	0.0271 (259)	0.0248 (120)	6 10	3	3
	0.0146 (121)	0.0321 (286)	. ,	9	3	3
Sebring, FL	0.0115 (180)	0.0421 (317)	0.0579 (12)			
St. George, UT Steelster Ledi CA	0.0558 (2)	0.0303 (274)	0.0457 (19)	3	3	3
Stockton-Lodi, CA	0.0137 (139)	0.0208 (202)	0.0217 (167)	11		3
Tampa-St. Petersburg-Clearwater, FL	0.0136 (144)	0.0305 (275)	0.0258 (109)	5	3	3
Valdosta, GA	0.0145 (125)	0.0233 (222)	0.0286 (76)	10	3	3
Vallejo-Fairfield, CA	0.0122 (169)	0.0244 (233)	0.0266 (93)	8	3	3
Wilmington, NC	0.0232 (33)	0.0229 (218)	0.0216 (168)	5	3	3
Yuma, AZ	0.0198 (59)	0.0243 (231)	0.0466 (18)	9	3	3
Albuquerque NM	0.0125 (146)	0.0108 (102)	0.0151 (285)	Count 7	4	48
Albuquerque, NM Corvallis, OR	0.0135 (146) 0.0116 (179)	0.0198 (192) 0.0252 (238)	0.0151 (285)	3	4	3
Jackson, TN	. ,		. ,	9	4	
,	0.0145 (124)	0.0209 (203)	0.0186 (219)	-		3
Medford, OR	0.0177 (73)	0.0265 (255)	0.0199 (199)	10	4	3
Modesto, CA	0.0117 (176)	0.0221 (212)	0.0201 (196)	10	4	3
Pensacola-Ferry Pass-Brent, FL	0.0111 (191)	0.0240 (228)	0.0143 (299)	9	4	4
Santa Fe, NM	0.0137 (141)	0.0297 (269)	0.0168 (248)	6	4	3
Tucson, AZ	0.0141 (129)	0.0263 (253)	0.0191 (212)	9	4	3
Wausau, WI	0.0123 (168)	0.0203 (196)	0.0164 (260)	6	4	3
Ann Arbor, MI	0.0072 (251)	0.0146 (145)	0.0253 (114)	Count 7	5	9 7
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Beckley, WV	0.0070 (254)	0.0166 (163)	0.0238 (136)	11	5	7
Bloomington, IL	0.0098 (212)	0.0185 (181)	0.0387 (28)	9	5	7
Burlington-South Burlington, VT	0.0105 (205)	0.0086 (68)	0.0214 (170)	6	5	5
Carbondale-Marion, IL	0.0110 (194)	0.0116 (102)	0.0276 (83)	9	5	3
Dubuque, IA	0.0110 (196)	0.0081 (61)	0.0296 (67)	11	5	1
Enid, OK	0.0065 (260)	0.0178 (177)	0.0327 (47)	10	5	7

Evansville, IN-KY 0.0056 (277) 0.0133 (189) 0.0214 (173) 10 5 7 Jefferson City, MO 0.0108 (198) 0.0148 (149) 0.0214 (173) 10 5 3 Jopins, MO 0.0101 (130) 0.0184 (189) 0.0236 (151) 10 5 7 Kanakaee, IL 0.0091 (224) 0.0184 (189) 0.0238 (151) 10 5 7 Kanakaee, IL 0.0022 (216) 0.0128 (111) 0.0109 (233) 8 6 8 Alkanos, TA 0.0022 (221) 0.0120 (111) 0.0109 (233) 8 6 8 Alkanos, Schenectady, Proy, YY 0.0046 (233) 0.0107 (56) 0.0101 (330) 8 6 8 Alkanos, Fachenectady, Proy, YY 0.0046 (223) 0.0147 (135) 0.012 (337) 8 6 8 Alkanos, Fachenectady, Proy, YY 0.0046 (223) 0.0141 (303) 7 6 8 Alkanos, Fachenectady, Proy, YY 0.0046 (234) 0.0141 (303) 7 6 8 Alkanos, Fachenectady, Proy, YY	Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
Johnson Civ, TN 0.0111 (193) 0.0184 (180) 0.0236 (138) 7 5 3 Joplin, MO 0.0102 (207) 0.0163 (157) 0.0230 (151) 10 5 7 Rankakce, IL 0.0091 (224) 0.0180 (179) 0.0230 (151) 10 5 7 Lewiston-Auburn, ME 0.0059 (271) 0.0186 (182) 0.0230 (151) 6 5 7 Marcester, MA-CT 0.0062 (266) 0.0178 (174) 0.0200 (136) 8 6 8 Albary-Schenectady-Troy, NY 0.0046 (230) 0.0107 (56) 0.0104 (585) 5 6 6 Allentovn-Heinhehm-Faxton, PA-NJ 0.0051 (255) 0.0121 (237) (308) 8 6 8 Balimore-Columbia-Towon, MD 0.0064 (262) 0.0140 (138) 0.0121 (337) (38) 8 6 8 Chantanoga, TN-GA 0.0086 (237) 0.0145 (142) 0.0141 (303) 7 6 8 Chantanoca, DH-KY-IN 0.0082 (241) 0.0141 (303) 7 6 8 Chantanoca, TN-GA 0.0086 (232)	Evansville, IN-KY	0.0056 (277)	0.0193 (188)	0.0220 (163)	3	5	7
Joplin, MO 0.0102 (207) 0.0163 (157) 0.0207 (186) 5 5 7 Kankakee, IL 0.0091 (224) 0.0181 (179) 0.0230 (151) 10 5 7 Worcester, MA-CT 0.0062 (266) 0.0178 (174) 0.0209 (180) 7 5 7 Abliene, TX 0.0092 (221) 0.0116 (133) 8 6 8 Ablieny, Schenectady-Troy, NY 0.0046 (293) 0.0106 (1360) 8 6 6 Allontown-Bethlehem-Easton, PA-NJ 0.0087 (230) 0.0116 (308) 8 6 8 Algosta-Richmond County, GA-SC 0.0056 (276) 0.0119 (199) 0.0121 (335) 8 6 8 Baltimore-Columbia-Towson, MD 0.0044 (218) 0.0119 (119) 0.0141 (303) 7 6 8 Chartanoga, TN-GA 0.0086 (232) 0.0198 (191) 0.0141 (303) 7 6 8 Chartanoga, TN-GA 0.0086 (232) 0.0191 (919) 0.0141 (303) 7 6 8 Charatanoga, TN-GA 0.00802 (221)	Jefferson City, MO	0.0108 (198)	0.0148 (149)	0.0214 (173)	10	5	3
Kankake, IL 0.0091 (224) 0.0181 (179) 0.0230 (151) 10 5 7 Lewiston-Auhurn, ME 0.0059 (271) 0.0186 (182) 0.0233 (79) 6 5 7 Vorcester, MA-CT 0.0005 (271) 0.0186 (182) 0.0233 (79) 6 5 7 Vorcester, MA-CT 0.0002 (221) 0.0120 (111) 0.0109 (353) 8 6 8 Ableno, TX 0.0092 (221) 0.0101 (010) 0.0101 (360) 8 6 6 Albary-Schenectaly-Troy, NY 0.0005 (285) 0.0101 (010) 0.0104 (333) 1 6 8 Algustar-Richmond County, GA-SC 0.0055 (287) 0.0114 (138) 0.0121 (335) 8 6 8 Baltimore-Columbia-Towson, MD 0.0044 (220) 0.0114 (130) 0.0194 (133) 7 6 8 Chamapign-Urbana, IL 0.0047 (221) 0.0141 (303) 7 6 8 Chamapign-Urbana, IL 0.0047 (321) 0.014 (488) 0.0120 (338) 9 6 6 Chamapign-Urbana	Johnson City, TN	0.0111 (193)	0.0184 (180)	0.0236 (138)	7	5	3
Lewiston-Auburn, ME 0.0059 (27) 0.0186 (182) 0.0283 (79) 6 5 7 Worcester, MA-CT 0.006 (266) 0.0178 (174) 0.0299 (180) 7 5 7 Marcester, MA-CT 0.0062 (261) 0.0178 (174) 0.0209 (180) 7 5 7 Ablamy-Schenetrady-Troy, NY 0.0046 (233) 0.0106 (1) 0.0101 (360) 8 6 8 Alleatown-Bethlehem-Easton, PA-NJ 0.0085 (276) 0.0106 (358) 5 6 6 Alleatown-Bethlehem-Easton, PA-NJ 0.0054 (276) 0.0119 (109) 0.0120 (337) 11 6 8 Baltimore-Cloumbin-Towson, MD 0.0064 (218) 0.0114 (189) 0.00124 (335) 7 6 7 Charanogan, TM-GA 0.0083 (237) 0.0144 (142) 0.0113 (349) 5 6 8 Clanimati, OH-KY-IN 0.0084 (231) 0.0144 (88) 0.0120 (338) 9 6 6 Davenprot-Mointe-Rock Island, IA-IL 0.0041 (420) 0.0184 (142) 0.0113 (139) 5 6 8	Joplin, MO	0.0102 (207)	0.0163 (157)	0.0207 (186)	5	5	7
Worester, MA-CT 0.0062 (26) 0.0178 (174) 0.0209 (180) 7 5 7 Courn 14 Abliene, TX 0.0029 (221) 0.0120 (110) 0.019 (333) 8 6 8 Albany-Schenectady-Troy, NY 0.0046 (293) 0.0106 (91) 0.0101 (360) 8 6 6 Allentow-Bethlehem-Easton, PA-NJ 0.0087 (230) 0.0077 (56) 0.0113 (303) 8 6 8 Allentow-Bethlehem-Easton, PA-NJ 0.0085 (235) 0.0132 (128) 0.0113 (303) 8 6 8 Baltimore-Columbia-Towon, MD 0.0044 (22) 0.0114 (189) 0.0012 (37) 11 6 8 Boiomington, IN 0.0094 (218) 0.0119 (110) 0.0194 (205) 7 6 7 Champaign-Urbana, IL 0.0047 (232) 0.0141 (103) 0.033 (31) 8 6 8 Champaign-Urbana, IL 0.0041 (302) 0.0148 (185) 0.0123 (31) 8 6 8 Champaign-Urbana, ID+V 0.0076 (247) 0.0118 (106) 0.0124 (32) </td <td>Kankakee, IL</td> <td>0.0091 (224)</td> <td>0.0181 (179)</td> <td>0.0230 (151)</td> <td>10</td> <td>5</td> <td>7</td>	Kankakee, IL	0.0091 (224)	0.0181 (179)	0.0230 (151)	10	5	7
Control Count 14 Abilene, TX 0.0092 (221) 0.0120 (111) 0.0109 (353) 8 6 Albury-Schenetady-Troy, NY 0.0047 (230) 0.0106 (358) 5 6 6 Allentown-Bethlehem-Easton, PA-NJ 0.0051 (285) 0.0132 (128) 0.0137 (088) 8 6 8 Balimore-Columbia-Towson, MD 0.0064 (262) 0.0140 (138) 0.0121 (335) 8 6 8 Balomigton, IN 0.0042 (218) 0.0149 (109) 0.0120 (337) 7 6 8 Chanangia, Th-GA 0.0086 (232) 0.0198 (191) 0.0114 (303) 7 6 8 Chanangia, Th-GA 0.0081 (237) 0.0145 (142) 0.0113 (349) 5 6 8 Chanangia, Th-GA 0.0041 (302) 0.0188 (185) 0.0136 (313) 8 6 8 2 Chananoga, TN-GA 0.0071 (247) 0.0114 (88) 0.0122 (332) 9 6 6 Dawenport-Moline-Rock Island, IA-IL 0.0041 (302) 0.0188 (185) 0.016 (231)	Lewiston-Auburn, ME	0.0059 (271)	0.0186 (182)	0.0283 (79)	6	5	7
Abilene, TX 0.0092 (221) 0.0120 (111) 0.0109 (353) 8 6 8 Albary-Schenectady-Troy, NY 0.0046 (293) 0.0106 (91) 0.0101 (360) 8 6 6 Albartow-Bethlem-Easton, PA-NJ 0.0051 (285) 0.012 (128) 0.0117 (368) 8 6 8 Algonza-Richmond County, GA-SC 0.0056 (276) 0.0119 (109) 0.0124 (133) 11 6 8 Baltimore-Columbia-Towson, MD 0.0046 (262) 0.0140 (138) 0.0121 (335) 8 6 8 Boomington, IN 0.0047 (218) 0.0119 (110) 0.0194 (205) 7 6 7 Chartanooga, TN-GA 0.0086 (232) 0.0194 (142) 0.0133 (349) 5 6 8 Cuncinstri, OH-KY-IN 0.0032 (321) 0.014 (142) 0.0132 (321) 12 6 8 Cuncinstri, OH-KY-IN 0.0032 (321) 0.014 (130) 0.013 (31) 8 6 8 Cuncinstri, OH-KY-IN 0.004 (241) 0.018 (185) 0.013 (213) 16 6 8	Worcester, MA-CT	0.0062 (266)	0.0178 (174)	0.0209 (180)	7	5	7
Albany-Schenectady-Troy, NY 0.0046 (293) 0.0106 (91) 0.011 (360) 8 6 6 Allentown-Bethlehem-Easton, PA-NI 0.0087 (230) 0.0017 (56) 0.0106 (258) 8 6 8 Allentown-Bethlehem-Easton, PA-NI 0.0056 (276) 0.0119 (109) 0.0123 (337) 11 6 8 Baltimore-Columbia-Towson, MD 0.0064 (262) 0.0119 (110) 0.0194 (205) 7 6 7 Champaign-Urbana, IL 0.0047 (211) 0.0194 (189) 0.0085 (371) 8 6 8 Chatranooga, TN-GA 0.0086 (232) 0.0198 (191) 0.0114 (303) 7 6 8 Clincinati, OH-KY-IN 0.0023 (234) 0.0140 (488) 0.0120 (338) 9 6 6 Davenport-Moline-Rock Island, IA-IL 0.0041 (302) 0.0188 (185) 0.0136 (313) 8 6 8 Glens Falls, NT 0.0084 (234) 0.0068 (43) 0.0163 (261) 12 6 5 Harrisburg-Carlisle, PA 0.0070 (255) 0.0090 (77) 0.0092 (355) 9 6 6 Harrisburg-Carlisle, PA 0.0016 (294) <t< td=""><td></td><td></td><td></td><td></td><td>Count</td><td></td><td>14</td></t<>					Count		14
Albany-Schenectady-Troy, NY 0.0046 (293) 0.0106 (91) 0.011 (360) 8 6 6 Allentown-Bethlehem-Easton, PA-NI 0.0087 (230) 0.0017 (56) 0.0106 (258) 8 6 8 Allentown-Bethlehem-Easton, PA-NI 0.0056 (276) 0.0119 (109) 0.0123 (337) 11 6 8 Baltimore-Columbia-Towson, MD 0.0064 (262) 0.0119 (110) 0.0194 (205) 7 6 7 Champaign-Urbana, IL 0.0047 (211) 0.0194 (189) 0.0085 (371) 8 6 8 Chatranooga, TN-GA 0.0086 (232) 0.0198 (191) 0.0114 (303) 7 6 8 Clincinati, OH-KY-IN 0.0023 (234) 0.0140 (488) 0.0120 (338) 9 6 6 Davenport-Moline-Rock Island, IA-IL 0.0041 (302) 0.0188 (185) 0.0136 (313) 8 6 8 Glens Falls, NT 0.0084 (234) 0.0068 (43) 0.0163 (261) 12 6 5 Harrisburg-Carlisle, PA 0.0070 (255) 0.0090 (77) 0.0092 (355) 9 6 6 Harrisburg-Carlisle, PA 0.0016 (294) <t< td=""><td>Abilene, TX</td><td>0.0092 (221)</td><td>0.0120 (111)</td><td>0.0109 (353)</td><td>8</td><td>6</td><td>8</td></t<>	Abilene, TX	0.0092 (221)	0.0120 (111)	0.0109 (353)	8	6	8
Altoona, PA 0.0051 (285) 0.0132 (128) 0.0137 (308) 8 6 8 Algusta-Richmond County, GA-SC 0.0056 (276) 0.0119 (109) 0.0120 (337) 11 6 8 Baltimore-Columbia-Towson, MD 0.0064 (262) 0.0119 (109) 0.0121 (335) 8 6 8 Boomington, IN 0.0004 (218) 0.0119 (109) 0.0014 (205) 7 6 7 Chattanooga, TN-GA 0.0086 (322) 0.0198 (191) 0.0114 (303) 7 6 8 Cumberland, MD-WV 0.0028 (324) 0.0104 (88) 0.0123 (331) 8 6 8 Duluth, MN-WI 0.0076 (247) 0.0118 (106) 0.0124 (332) 12 6 8 Glens Falls, NT 0.0084 (234) 0.0163 (184) 0.0163 (355) 9 6 8 Hurrisburg-Cartilse, PA 0.0070 (255) 0.0090 (77) 0.0092 (355) 9 6 8 Interiasburg-Cartilse, PA 0.0010 (264) 0.0116 (139) 0.0119 (342) 7 6 8	Albany-Schenectady-Troy, NY	0.0046 (293)	0.0106 (91)	0.0101 (360)	8	6	6
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Walla Walla, WA 0.0089 (228) 0.0091 (78) 0.0202 (194) 12 6 5 Waterloo-Cedar Falls, IA 0.0094 (217) 0.0069 (45) 0.0164 (258) 12 6 5 Wheeling, WV-OH 0.0028 (325) 0.0104 (87) 0.0136 (312) 8 6 6	Urban Honolulu, HI	0.0061 (268)	0.0153 (153)	0.0134 (316)	6	6	8
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Wheeling, WV-OH 0.0028 (325) 0.0104 (87) 0.0136 (312) 8 6 6	Walla Walla, WA	0.0089 (228)	0.0091 (78)	0.0202 (194)	12	6	5
	Waterloo-Cedar Falls, IA	0.0094 (217)	0.0069 (45)	0.0164 (258)	12	6	5
York-Hanover, PA 0.0053 (282) 0.0178 (178) 0.0155 (278) 7 6 7	Wheeling, WV-OH	0.0028 (325)	0.0104 (87)	0.0136 (312)	8	6	6
	York-Hanover, PA	0.0053 (282)	0.0178 (178)	0.0155 (278)	7	6	7

Alexandria, LA 0.0096 (214) 0.021 (27) 0.0226 (154) 7 7 7 Anniston-Oxford-Jacksonville, AL 0.0090 (357) 0.0487 (337) 0.0200 (102) 12 7 7 Adamite City-Harmonton, NJ 0.0023 (533) 0.0214 (178) 0.0682 8) 5 7 7 Baumort-Port Arthur, TX 0.0056 (275) 0.0214 (209) 0.0288 (27) 6 7 7 Cape Girandeau, MO-II. 0.0063 (236) 0.0374 (29) 0.0288 (23) 0.739 (5) 14 7 3 Columbus, GA-AL 0.0008 (157) 0.0324 (158) 0.0326 (158) 0.0214 (168) 5 7 7 Daton, GA 0.0049 (288) 0.0681 (399) 0.0218 (166) 5 7 7 Daton, GA 0.0049 (231) 0.0426 (212) 0.024 (126) 7 7 7 Decatur, IL 0.0015 (203) 0.0408 (314) 0.0250 (116) 6 7 7 7 Decatur, IL 0.0016 (337) 0.0341 (23) 0.0404 (24) 4 </th <th>Metropolitan Statistical Area</th> <th>Growth (Rank)</th> <th>Instability (Rank)</th> <th>Resilience (Rank)</th> <th>Down turns</th> <th>C 1</th> <th>C 2</th>	Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
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Santa Cruz-Watsonville, CA 0.0027 (328) 0.0469 (331) 0.0226 (153) 6 7 7	San Jose-Sunnyvale-Santa Clara, CA	0.0080 (241)	0.0957 (375)	0.0331 (44)	3	7	7
	Santa Cruz-Watsonville, CA	0.0027 (328)	0.0469 (331)	0.0226 (153)	6	7	7

Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
Sheboygan, WI	0.0072 (252)	0.0308 (278)	0.0262 (97)	6	7	7
Sherman-Denison, TX	0.0079 (243)	0.0298 (270)	0.0243 (128)	7	7	7
Sierra Vista-Douglas, AZ	0.0096 (215)	0.0267 (257)	0.0300 (62)	8	7	7
Spartanburg, SC	0.0085 (233)	0.0296 (268)	0.0254 (113)	9	7	7
Springfield, IL	-0.0009 (358)	0.1024 (376)	0.0596 (10)	8	7	7
Springfield, OH	-0.0033 (373)	0.0889 (372)	0.0294 (69)	5	7	7
Sumter, SC	0.0031 (316)	0.0796 (369)	0.0340 (39)	5	7	7
Tallahassee, FL	0.0102 (208)	0.0243 (230)	0.0328 (46)	8	7	7
Williamsport, PA	0.0006 (345)	0.0253 (242)	0.0221 (162)	8	7	7
Youngstown-Warren-Boardman, OH-PA	-0.0044 (375)	0.0788 (366)	0.0353 (37)	6	7	7
Yuba City, CA	0.0072 (250)	0.0309 (279)	0.0270 (90)	12	7	7
	~ /	~ /		Count		61
Akron, OH	0.0060 (269)	0.0212 (207)	0.0107 (357)	6	8	8
Albany, GA	0.0034 (315)	0.0470 (332)	0.0090 (367)	3	8	8
Bangor, ME	0.0028 (326)	0.0210 (205)	0.0112 (352)	7	8	8
Bay City, MI	-0.0008 (356)	0.0723 (361)	0.0101 (362)	2	8	8
Binghamton, NY	-0.0060 (379)	0.0850 (370)	0.0000 (379)	1	8	8
Birmingham-Hoover, AL	0.0062 (267)	0.0244 (232)	0.0151 (288)	3	8	7
Blacksburg-Christiansburg-Radford, VA	0.0049 (289)	0.0235 (223)	0.0196 (203)	5	8	7
Bloomsburg-Berwick, PA	0.0048 (290)	0.0210 (204)	0.0176 (234)	9	8	7
Boston-Cambridge-Newton, MA-NH	0.0068 (258)	0.0299 (272)	0.0120 (339)	3	8	8
Bridgeport-Stamford-Norwalk, CT	0.0005 (346)	0.0372 (307)	0.0192 (209)	4	8	7
Buffalo-Cheektowaga-Niagara Falls, NY	0.0006 (344)	0.0206 (200)	0.0071 (377)	3	8	8
Burlington, NC	0.0030 (321)	0.0653 (354)	0.0193 (207)	6	8	7
Canton-Massillon, OH	0.0010 (340)	0.0550 (347)	0.0126 (331)	4	8	8
Chambersburg-Waynesboro, PA	0.0077 (246)	0.0254 (243)	0.0160 (270)	3	8	7
Charleston, WV	0.0001 (348)	0.0310 (280)	0.0131 (321)	6	8	8
Chicago-Naperville-Elgin, IL-IN-WI	0.0054 (278)	0.0206 (201)	0.0160 (269)	6	8	7
Cleveland-Elyria, OH	-0.0003 (352)	0.0581 (349)	0.0179 (230)	2	8	7
Detroit-Warren-Dearborn, MI	0.0014 (339)	0.0777 (363)	0.0163 (264)	4	8	7
Dothan, AL	0.0031 (320)	0.0390 (311)	0.0149 (290)	6	8	7
Elmira, NY	-0.0047 (376)	0.0782 (364)	0.0203 (193)	5	8	7
Florence, SC	0.0042 (301)	0.0380 (310)	0.0086 (370)	5	8	8
Fond du Lac, WI	0.0057 (273)	0.0278 (263)	0.0192 (210)	8	8	7
Gulfport-Biloxi-Pascagoula, MS	0.0097 (213)	0.0522 (344)	0.0177 (232)	5	8	7
Hartford-West Hartford-East Hartford, CT	-0.0012 (361)	0.0655 (355)	0.0000 (379)	1	8	8
Johnstown, PA	-0.0026 (371)	0.0305 (276)	0.0112 (351)	4	8	8
Kalamazoo-Portage, MI	0.0044 (297)	0.0219 (210)	0.0116 (346)	5	8	8
Kingsport-Bristol-Bristol, TN-VA	0.0022 (333)	0.0229 (219)	0.0120 (340)	5	8	8
Lansing-East Lansing, MI	0.0031 (319)	0.0371 (306)	0.0189 (214)	7	8	7
Los Angeles-Long Beach-Anaheim, CA	0.0028 (323)	0.0474 (334)	0.0144 (296)	4	8	8
Lynchburg, VA	0.0034 (314)	0.0326 (289)	0.0184 (222)	6	8	7
Manchester-Nashua, NH	0.0068 (259)	0.0231 (220)	0.0166 (254)	5	8	7
Memphis, TN-MS-AR	0.0091 (226)	0.0226 (214)	0.0086 (369)	9	8	8
Michigan City-La Porte, IN	-0.0026 (369)	0.0591 (350)	0.0118 (345)	5	8	8
Midland, MI	0.0046 (292)	0.0204 (197)	0.0086 (368)	5	8	8
Monroe, LA	0.0092 (223)	0.0204 (197)	0.0098 (363)	5	8	8
Monroe, MI	0.0075 (248)	0.0536 (346)	0.0165 (257)	8	8	7
Montgomery, AL	0.0083 (238)	0.0253 (241)	0.0103 (237)	7	8	7
New Bern, NC	0.0091 (225)	0.0233 (241)	0.0171 (240)	8	8	7
New Haven-Milford, CT	-0.0003 (354)	0.0317 (283)	0.0131 (287)	4	8	8
	-0.0003 (334)	0.0344 (297)	0.0130 (323)	4	0	0

Metropolitan Statistical Area	Growth (Rank)	Instability (Rank)	Resilience (Rank)	Down turns	C 1	C 2
New Orleans-Metairie, LA	-0.0001 (349)	0.0677 (357)	0.0083 (373)	7	8	8
New York-Newark-Jersey City, NY-NJ-PA	0.0050 (287)	0.0240 (227)	0.0129 (326)	3	8	8
Niles-Benton Harbor, MI	-0.0007 (355)	0.0866 (371)	0.0204 (192)	4	8	7
Ocean City, NJ	0.0058 (272)	0.0318 (285)	0.0192 (211)	12	8	7
Peoria, IL	0.0038 (309)	0.0256 (245)	0.0189 (213)	9	8	7
Pine Bluff, AR	-0.0049 (377)	0.0565 (348)	0.0140 (305)	6	8	8
Pittsfield, MA	-0.0011 (360)	0.0433 (323)	0.0000 (379)	1	8	8
Providence-Warwick, RI-MA	0.0031 (318)	0.0266 (256)	0.0154 (281)	7	8	7
Reading, PA	0.0038 (310)	0.0202 (195)	0.0079 (374)	10	8	8
Redding, CA	0.0081 (240)	0.0410 (315)	0.0185 (220)	8	8	7
Rochester, NY	0.0017 (336)	0.0252 (239)	0.0187 (217)	7	8	7
Rockford, IL	0.0008 (343)	0.0513 (342)	0.0197 (202)	6	8	7
Rome, GA	0.0039 (307)	0.0511 (341)	0.0092 (366)	6	8	8
Saginaw, MI	-0.0012 (362)	0.0681 (358)	0.0137 (310)	5	8	8
Santa Maria-Santa Barbara, CA	0.0053 (279)	0.0224 (213)	0.0159 (271)	8	8	7
Sioux City, IA-NE-SD	0.0078 (245)	0.0205 (198)	0.0108 (354)	8	8	8
South Bend-Mishawaka, IN-MI	0.0031 (317)	0.0490 (338)	0.0113 (350)	7	8	8
Springfield, MA	0.0025 (329)	0.0314 (282)	0.0137 (311)	4	8	8
St. Joseph, MO-KS	0.0082 (239)	0.0201 (194)	0.0166 (253)	7	8	7
St. Louis, MO-IL	0.0040 (306)	0.0211 (206)	0.0114 (348)	5	8	8
Staunton-Waynesboro, VA	0.0043 (300)	0.0272 (260)	0.0158 (272)	6	8	7
Syracuse, NY	-0.0010 (359)	0.0298 (271)	0.0074 (376)	2	8	8
Terre Haute, IN	0.0015 (338)	0.0466 (330)	0.0116 (347)	4	8	8
Texarkana, TX-AR	0.0041 (304)	0.0227 (215)	0.0145 (293)	6	8	7
Toledo, OH	0.0021 (334)	0.0534 (345)	0.0169 (247)	3	8	7
Topeka, KS	0.0040 (305)	0.0366 (305)	0.0118 (344)	4	8	8
Trenton, NJ	0.0062 (265)	0.0214 (208)	0.0184 (225)	9	8	7
Utica-Rome, NY	-0.0002 (350)	0.0355 (303)	0.0142 (301)	4	8	8
Vineland-Bridgeton, NJ	0.0009 (342)	0.0350 (300)	0.0157 (275)	7	8	7
Watertown-Fort Drum, NY	0.0010 (341)	0.0323 (287)	0.0084 (372)	4	8	8
Weirton-Steubenville, WV-OH	-0.0107 (382)	0.1046 (377)	0.0000 (379)	1	8	8
Wichita Falls, TX	0.0029 (322)	0.0274 (261)	0.0184 (226)	5	8	7
Wichita, KS	0.0063 (263)	0.0262 (251)	0.0185 (221)	7	8	7
Winston-Salem, NC	0.0053 (280)	0.0317 (284)	0.0170 (244)	6	8	7
				Count		73
				Total		382

Notes.

Growth and resilience indices are shown in raw values and its ranks are assigned in descending order: Greater the value, higher the rank. Highly ranked metros are deemed to grow faster and be more resilient.

Instability indices are shown in raw values while its ranks are assigned in ascending order: Smaller the value, higher the rank. Highly ranked metros are deemed to be more stable.

Column C 1 denotes categories based on median indices (see Table 4).

Column C 2 denotes categories based on nationwide metropolitan averages (see Table 5).