CROSS-SCALE DYNAMICS OF A REGIONAL URBAN SYSTEM THROUGH TIME

Tarsha EASON* and Ahjond S. GARMESTANI*

Abstract **-** *Urban systems have been the subject of investigation for over a century. From central place and hierarchy theory to Gibrat's and Zipf's law, urban systems have been subjected to intense scrutiny. More recently, in a series of papers analyzing urban systems from the perspective of resilience and panarchy theory, urban systems have been characterized as scale-dependent. In this work, we examined the relationships between city size, growth rates, and the key factors that impact resilience and population dynamics in a regional urban system over time. Results of this work indicate that while there are similarities between cities, certain factors appear to be more important in one place than another, and that city growth is not random, but rather, correlated with key factors. In particular, we found that city growth was driven by mean household income and the percentage of the population of a city with a college degree.*

Key-words: URBAN SYSTEMS; CROSS-SCALE RESILIENCE; GROWTH RATES; CITY SIZE DISTRIBUTIONS; INFORMATION THEORY

Classification JEL: R00, C02, J11

Acknowledgements *- This line of research on resilience (cross-scale dynamics and structure) in urban systems is dedicated to the memory of K.M. Bessey.*

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INTRODUCTION

Urban systems have been the subject of investigation for over a century. From central place and hierarchy theory to Gibrat's and Zipf's law, urban systems have been subjected to intense scrutiny. More recently, in a series of papers analyzing urban systems from the perspective of resilience and panarchy theory, urban systems have been characterized as scale-dependent. We review this series of papers in the following section in order to preface the research presented in this manuscript.

Bessey (2002) theorized that the spacing of cities on a national scale is driven by a slow dynamic. In essence, functional processes act as corollaries of the "slaving principle" in which large, slow processes (e.g., national economies) enslave smaller, faster processes (e.g., regional and city economies) (Bessey, 2002). The landscape provides locations, such as valleys or natural harbors, which favor agglomeration (Brakman et al., 2001), and social-ecological systems (such as cities) self-organize, with the manifestation of size (population) reflecting the limitations of the landscape (Berkes and Folke, 1998). For example, the rise of a city like Phoenix, Arizona, may have been the result of a vacuum of urbanization in the southwestern region of the United States, combined with access to a critical resource (e.g., water) for city growth and development. At a regional scale, a fast variable driven by the minimum population and income needed for city survival also influences city size (Bessey, 2002). The results reported in Garmestani et al. (2007) confirm Bessey's speculation, and furthermore demonstrate that panarchy manifests in urban systems, at least at a regional scale.

With respect to panarchy, ecological dynamics can be explained in a simplified manner by three sets of variables operating at different speeds (Holling et al., 2008). In forests, for example, insects and conifer needles are "fast" variable (one-year generation time), tree crowns are intermediate speed variables (12-15 year generation time), and trees are "slow" variables (100+ years generation time) (Holling et al., 2008). The distinctness of the speed of these variables in ecosystems manifests in reinforcing, scale-dependent structure, similar to the structure that manifests in urban systems (Garmestani et al., 2009). For urban systems, city growth rates are the "fast" process, governance is an intermediate speed process, and infrastructure is a "slow" process (Holling et al., 2008).

Garmestani et al. (2005) analyzed data from the southwestern region of the United States and found that the distributions were discontinuous, as theorized by Bessey (2002). Bessey (2002) identified departures from a rank-size characterization (Zipf's Law; Zipf, 1949) of the city size data in the southeastern region of the United States. Using Bessey's data, Garmestani et al. (2007) performed a statistical hypothesis test upon rank-size city data from the southeastern region of the United States under the assumptions of Gibrat's Law (Gibrat, 1957). Zipf's Law manifests when all central places in an urban hierarchy have size-invariant growth rates. Thus, if Gibrat's Law is not satisified, Zipf's law cannot be satisfied. Garmestani et al. (2007) found that growth rates differed by city size, in contrast to the distribution expected if Gibrat's Law held for this data set. On a regional level, the results indicated that city growth was not driven by small, random growth forces. Rather, growth was correlated with size, with smaller cities exhibiting higher growth rates than average and larger cities exhibiting lower growth rates than average (Garmestani et al., 2007). The results reported in Garmestani et al. (2007) indicated that discrete size classes in city size distributions emerged as a result of size-dependent growth at the available scales of opportunity within urban systems.

Garmestani et al. (2008a) tested the overall city size distributions for the southeastern and southwestern United States (1990), as well as the individual size classes previously identified in Garmestani et al. (2008b) for power-law behavior. Power laws provided fits for overall city size distribution in the southeastern and southwestern regions of the United States. However, the overall city size distribution in the southeastern region of the United States exhibited a departure from power-law behavior in the upper tail. In addition, cities in the southeastern region self-organized into three discrete size classes, and the southwestern region was self-organized into six size classes. Each of these size classes was well described by power laws with differing slopes and intercepts. In the southeastern region of the United States, there was greater variability in the sizes of small cities when compared to the size class for large cities. With respect to the different power law fits for the individual size classes, the overall power law for the distribution did not capture evidence of the processes affecting city size at a finer scale of analysis, i.e., the individual size classes. Different power law fits for individual size classes support the proposition that different processes, e.g., growth rates, act upon cities at different scales. Garmestani et al. (2008a) interpreted the differences in the power law fits in the city size distributions as the manifestation of variable growth dynamics dependent upon city size. Complex systems can manifest multiple regimes (Gunderson et al., 2002), and size classes are evidence of multiple regimes within a system, whereas the power law fits for each size class are indicative of discrete ranges of scale at which cities are governed by similar processes. Garcia et al. (2011), also studying this dataset from the southeastern region of the United States, calculated transition probabilities for cities across all size classes. They found that short-term transition was chaotic in the small and medium size classes, but long-term transition across all size-classes revealed hierarchical system structure over time (i.e., cross-scale resilience) (Garcia et al., 2011).

In this work, we conducted an analysis of a regional urban system (southeastern United States) that has been the subject of research in the series of papers reviewed in the preceding sections. We used a U.S. census dataset incorporating the urbanized area (UA) definition. A UA comprises a central place and the urban fringe, which includes other "places" (Bessey, 2000). The Bureau of the Census officially defines a "place" as a concentration of population, which must have a name and be locally recognized, although it may or may not be legally incorporated under the laws of its state (Bessey, 2002). We analyzed a Bureau of Economic Analysis (BEA) dataset of cities in the southeastern region (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia and West Virginia) of the U.S.

for this research. The analysis of variables in this study that potentially influence dynamics in urban systems is based upon Information theory, in particular, a variation of Fisher information.

1. METHODS

Fisher information was developed by statistician Ronald Fisher (Fisher, 1922) as a measure of the information content in data and is focused on assessing patterns of behavior. Given that the existence of pattern signifies order, Fisher information has since been adapted to assess organizational complexity in the presence of imperfect observations, affording the ability to capture dynamic order (i.e., self-organization) in systems (Eason and Cabezas, 2012). In the context of resilience, dynamic order relates to the ability of a system to withstand perturbations and still maintain a steady state. This steady state may also be termed a regime and is characterized by a particular pattern of system behavior.

The form of Fisher information used in this work provides a means of monitoring system variables and collapsing them into a composite indicator that can be tracked over time to assess the dynamic behavior of systems to include its regimes and regime shifts. The theoretical foundation of Fisher information (described in detail by Fath et al., 2003 and Mayer et al., 2007) is denoted as :

$$I = \int \frac{1}{p(s)} \left[\frac{dp(s)}{ds} \right]^2 ds \qquad (1)$$

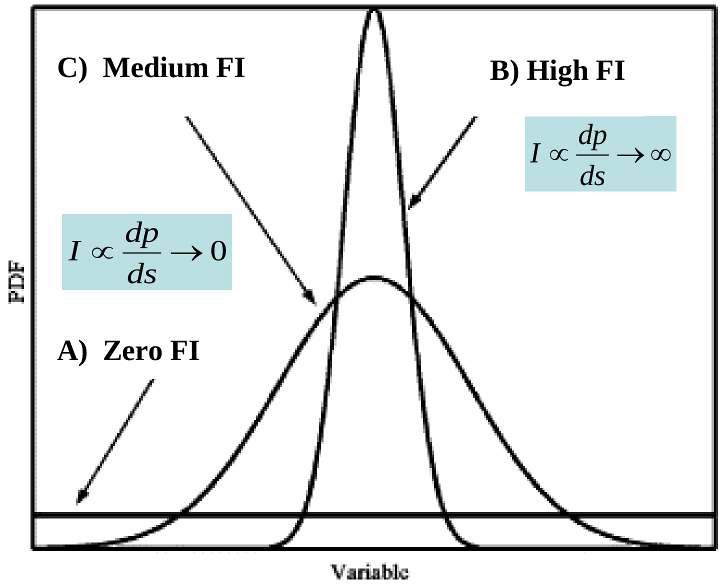
where, p(s) is the likelihood of observing a particular state (s) of the system. From Equation (1), Fisher information (henceforth denoted as FI) is proportional to the change in the probability of a system being in a particular state divided by the change in state (i.e., $dp(s)/ds$). To understand this concept, take a system characterized by completely random data. Such a system has no particular pattern, is unbiased toward any given state and consequently, has an equal probability of being in any state of the system resulting in a uniform probability density function (PDF) and an FI approaching zero (Fath et al., 2003) (Figure 1A).

On the other hand, a system defined by observable, consistent patterns (i.e., repeated measurements of the system over time results in the same state or condition) is highly orderly and biased toward a particular state or finite number of states; hence, it has a PDF with a steep slope and FI approaching infinity (Figure 1B). However, real systems exist between these two idealized extremes (Figure 1C). Further details of the analytical and numerical derivation of FI can be found in Mayer et al. (2007) and Karunanithi et al. (2008), respectively. US EPA (2010) also describes the computational aspects of using FI to assess system behavior. In the papers by Karunanithi et al. (2008), Eason and Cabezas (2012) and Gonzalez-Mejia et al. (2011), the authors invoke concepts pertinent to understanding resilient systems. They articulate the inherent nature of robust systems to adapt to change (i.e., self-organize) and describe the conditions of critical transitions to other dynamic regimes. Further, they apply FI and demonstrate the ability to use it to identify stable, resilient regimes and regime shifts as a function of dynamic order. Hence, here we formally propose FI as a measure of resilience in complex systems. Drawing from the sustainable regimes hypothesis which provides basic ideals for interpreting FI (Karunanithi et al., 2008), the statements are adapted to provide guidance for assessing system resilience. The modified statements are as follows: a) well functioning systems exist in ordered regimes in which the overall condition of the system is stable and results in a non-zero FI that does not change with time (i.e., $\frac{d\langle FI\rangle}{dt} \approx 0$, where <FI> indicates a mean FI value); b) steadily decreasing FI signifies progressive loss of dynamic order and denotes a system that is changing at a slower rate, losing functionality and thereby, losing resilience; and 3) a steadily increasing FI signifies a system that is changing more rapidly, yet still maintaining function; and 4) a steep decrease in FI between two stable dynamic regimes indicates a regime shift (Karunanithi et al., 2008). However, there is no guarantee that the latter regime is more humanly desirable than the former and requires further evaluation of the underlying variables characterizing the condition of the system (Eason and Cabezas, 2012). In other words, while the condition of the system state may be stable, the system may have organized into a less desirable state. Hence, FI allows us to assess the resilience of the system not the quality of its condition. In practice, FI has been applied to deriving fundamental equations of physics, thermodynamics, and population genetics (Frieden 1998, 2001). It was proposed by Cabezas and Fath (2002) as a sustainability metric and used to assess dynamic order and stability in complex model systems (Fath et al., 2003; Fath and Cabezas, 2004; Cabezas et al., 2005a, 2005b, Mayer et al., 2006). Further, FI was employed to optimize control of dynamic model systems for sustainable environmental management (Shastri et al., 2008a, 2008b), cancer immunotherapy and continuous isothermal crystallization (Rico-Ramirez et al., 2008). Recently, it has been used to detect and assess dynamic order, sustainability and regime shifts in real systems (Mayer et al., 2006; Karunanithi et al., 2008; Karunanithi et al., 2011; Gonzalez-Mejia et al., 2011; Eason and Cabezas, 2012).

2. DATA

This study involves the assessment of thirty one cities (Table 1) within the southeastern region of the United States from 1970 to 2010. In order to examine each city (system), pertinent variables were used to capture the condition (i.e., state) of the system over time. These variables were drawn from various studies (Glaeser, 2001; Glaeser and Saiz, 2003; Erickcek and McKinney, 2006 and Garmestani et al., 2007) and describe climatological, economic and demographic components of each system (Table 2). Data for the variables were compiled from multiple sources including the US Census Bureau and the National Climate Data Center, yet often were not available annually (Table 3). Hence, yearly time series were developed for each variable by interpolating where necessary.

Figure 1. Fisher information is proportional to dp/ds (adapted from Pawlowski and Cabezas, 2008)



Note :

A) *A system that has an equal probability of being in any state lacks order; accordingly, $I \to 0$ and represents the perfect disorder case.*

B) *The perfect order case occurs when a system is biased towards a state (or finite number of states). Since this system is more orderly, $I \to \infty$.*

C) *However, most systems exist between these two extremes.*

3. POPULATION GROWTH TRENDS FROM STUDY TO STUDY

Garmestani et al. (2007) identified the clustering of cities into size classes from 1860 to 1990 in the southeastern United States. However, the study also focused on the growth rates of cities. Hence, as a preliminary analysis, we compared the growth rate classes of the current data set to the classes in work done by Garmestani et al. (2007). The population growth rates were computed for each city over certain periods: EP (Garmestani et al. 2007 for the entire period, 1860 to 1990); RP (Garmestani et al., 2007 for the last two decades of the study, 1970 to 1990) and; CS (Current study from 1970 to 2010) and compared in Figure 2. Results indicate that the patterns of growth in the cities have changed over time resulting in a dramatic shift from a bias towards moderate to high population growth (EP) to a growth rate distribution skewed toward more cities experiencing growth of 10% or less per decade (CP). Moreover, note that in the overlapping period denoted by RP, the distribution has a near Gaussian shape. Such growth shifting is true in such cities as Atlanta, GA which experienced more shrinkage from 1970 to 1990 with modest growth since. Now that the growth patterns are clear and discernable, the question now becomes: what is driving changes in the patterns of growth. This work is focused on exploring the conditions of these cities to uncover their unique drivers of dynamic change.

Table 1. Matrix of Cities Assessed in Study

State	City					
Virginia	Alexandria: C1	Lynchburg: C13	Norfolk: C21	Petersburg: C24	Richmond: C26	
Georgia	Athens: C2	Atlanta: C3	Augusta: C4	Columbus: C8	Macon: C14	Savannah: C27
Louisiana	Baton Rouge: C5	New Orleans: C20				
South Carolina	Charleston: C6	Columbia: C7				
Florida	Key West: C9	Pensacola: C23				
Kentucky	Lexington: C10	Louisville: C12	Paducah: C22			
Arkansas	Little Rock: C11					
Tennessee	Memphis: C15	Nashville: C18				
Alabama	Mobile: C16	Montgomery: C17	Selma: C28			
Mississipi	Natchez: C19	Vicksburg: C29				
North Carolina	Raleigh: C25	Wilmington: C31				
West Virginia	Wheeling: C30					

Table 2. Variables used in the Study

Component	Variable
Climate	Avg. Annual Precip. Avg Annual Temp
Economic	Median Annual HH Income Percent Mfg. Worker Poverty Rate
Demographic	Percent College Percent HS Population

4. APPROACH

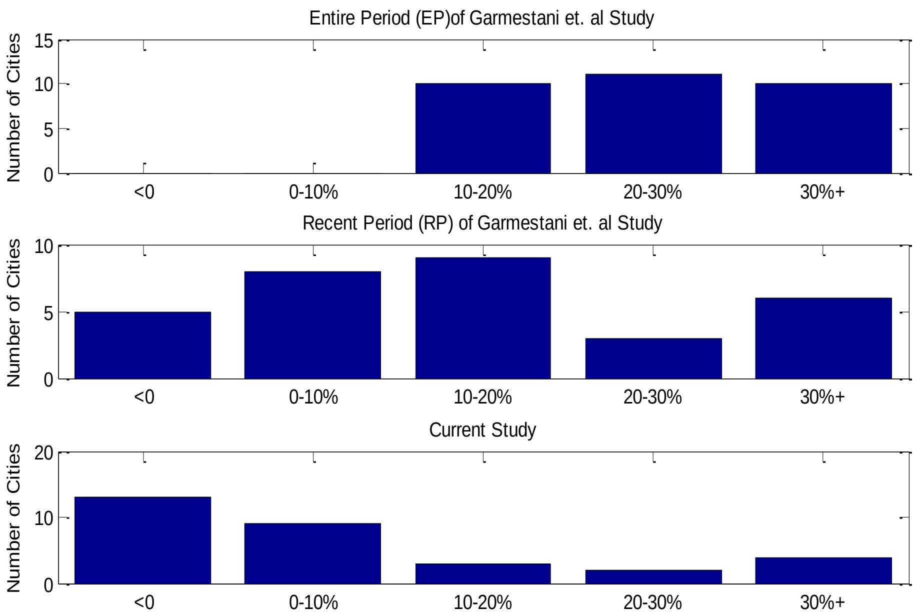
The dynamic changes in the cities understudy were assessed by computing FI from the variables characterizing each system. In accordance with the procedure implemented by Cabezas and Eason to use FI to assess the dynamic behavior of a regional ecosystem (USEPA, 2010), FI was calculated by setting up an eight year time bracket and moving the computation bracket forward one year at a time creating overlapping time windows. One FI value is produced per window and when calculated over the period of the study provides information necessary to evaluate the dynamic behavior of the system.

Table 3. Data Sources

#	Proxy/Surrogate	Component	Pillar	Details	2010 info
1	Average annual	Climate	ENV	http://www.ncdc.noaa.gov/ (TCTP and MNTM)	
2	Average annual	Climate	ENV	http://www.ncdc.noaa.gov/	
3	Median annual	Income	SOC-ECO	http://socds.huduser.org/Census/screen1.odb?metro=cbsa	2010 data: **http://quickfacts.cen**
4	Poverty rate	Income	SOC-ECO	http://socds.huduser.org/Census/screen1.odb?metro=cbsa	2010 data: **http://quickfacts.cen**
5	Share of persons 25	Educational	SOC	http://socds.huduser.org/Census/screen1.odb?metro=cbsa	2010 data: **http://quickfacts.cen**
6	Share of persons 25	Educational	SOC	http://socds.huduser.org/Census/screen1.odb?metro=cbsa	2010 data: **http://quickfacts.cen**
7	% Civilians employed in	Workforce	SOC-ECO	http://socds.huduser.org/Census/screen1.odb?metro=cbsa	2010 data: **http://quickfacts.cen**
8	Population	Population	SOC	http://socds.huduser.org/Census/screen1.odb?metro=cbsa	2010 data: **http://quickfacts.cen**

Legend: Variables used in Glaeser (2001)
Suggested variables from other sources

Figure 2. Population Growth Trends from Study to Study

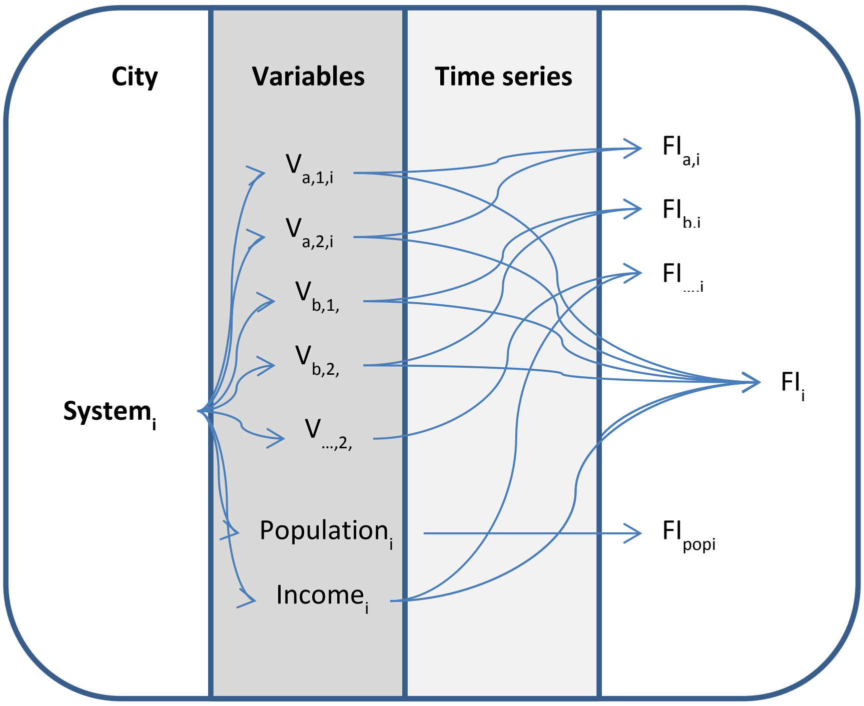


Note that EP: Entire Period of Garmestani & al. (2007) Study from 1860 to 1990; RP: Recent Period of Garmestani & al. (2007) from 1970 to 1990; CS: Current Study from 1970 to 2010.

5. RESULTS

There are two key concepts highlighted in the modified sustainable regimes hypothesis that are critically important for discussing the results of this study: mean and standard deviation of FI values over time. The FI results reported in Figure 4 illustrate the significance of the mean and variability in FI computations. Although higher FI is typically equated with higher order, in the context of resilience and stability, the level of order is not as important as the ability of the system to remain within a desirable regime. With this in mind, note that while the FI for Memphis, TN varied overtime, the values tended to settle around the mean thereby reflecting a level of stability. On the contrary, Wheeling, WV had a much larger range of deviation indicating loss of stability in the current regime and possibly, a regime shift to regime 1 from about 1977 to 1987, followed by a drop in FI, a transition period and then, regime 2 after 2005. Overall, when evaluating the mean of the FI computed for each city, we noted that the majority of the cities seemed to behave similarly with a mean FI within two standard deviations of the entire sample (Figure 5). However, Vicksburg, MS (C28) and Selma, AL (C29) deviated from this trend. Figure 6 provides a plot of the standard deviation of the FI for all of the cities. Aside from Memphis, TN (C15: lower) and Wheeling, WV (C30: higher), all of the cities were within 2σ of mean variation with Wheeling appearing to be the least stable of the cities under study.

Figure 3. Diagram of Approach to Analyzing Each City



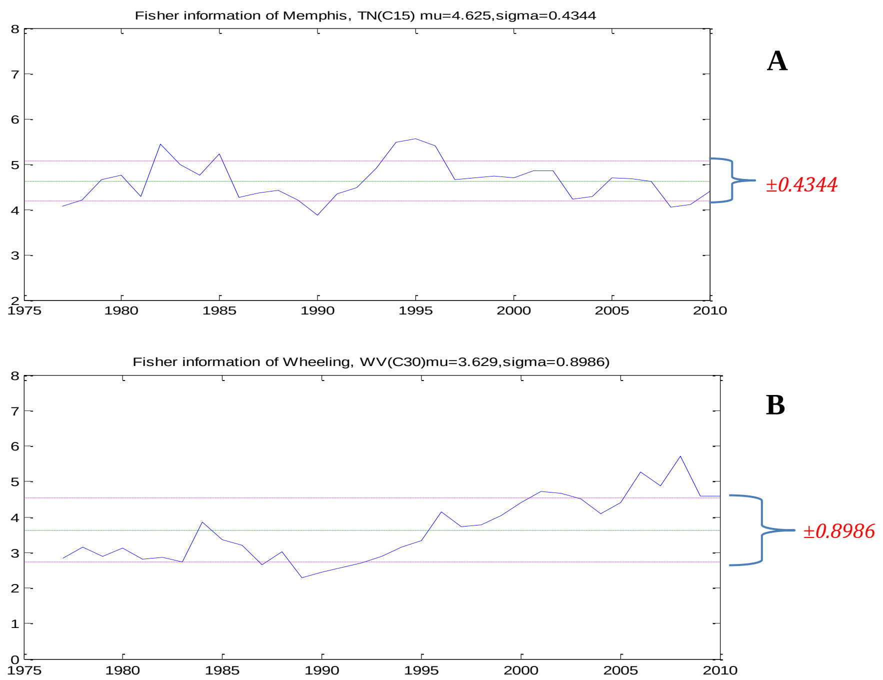
The following approach was employed to examine the potential factors driving (a) the resilience of the city and (b) population changes (Figure 3):

1. Compute FI for: (a) the overall system (i.e., each city), (b) each component (e.g., climate) and (c) population.

2. Use Spearman Rank Order Correlation (SROC) to compare: (a) FI of the system to the FI of the components to determine aspects impacting resilience; (b) FI of population to the FI of the components; and (c) the population to the remaining variables for each city to assess which variables are correlated with population changes.

3. Compute standard statistics to include the mean, standard deviation and coefficient of variation for the FI of each system.

Figure 4. Increased variation signifies loss of resilience



(A) Memphis, TN (μ=4.625, σ=0.4344)
(B) Wheeling, WV (μ=3.629, σ=0.8986).

To bring both of these concepts together, we designate the most resilient cities as those with a relatively high mean and low standard deviation in the FI result over time. This theory is explored in two ways: by calculating the coefficient of variation (CV: σ/μ) and plotting μFI vs. σFI. As a statistical measure of dispersion, the CV provides insight on the relative deviation in the FI values for each city.The CV of sixteen of the cities lies below the mean CV of all the cities with the highest ratio in Wheeling, WV (C30) and the lowest in Memphis, TN. The mean and standard deviation plots afford the ability to view both statistics which capture aspects of resilience simultaneously. The lower right quadrant of Figure 7 distinguishes twelve cities with a mean FI above the mean, and below the mean standard deviation (σ) of FI for all cities. Using the criteria established, the cities which are common for both measures include: Alexandria, VA, Athens, GA, Atlanta, GA, Augusta, GA-SC, Baton Rouge, LA, Charleston, SC, Columbia, SC, Columbus, GA-AL, Key West, FL, Lexington-Fayette KY, Little Rock, AR, Louisville, KY-IN, Lynchburg, VA, Macon, GA, Memphis, TN, Mobile, AL, Montgomery, AL, Nashville,TN, Natchez, MS, New Orleans, LA, Norfolk, VA, Paducah, KY, Pensacola, FL, Petersburg, VA. These cities are identified as the most resilient in the dataset.

Figure 5. Mean FI for all cities

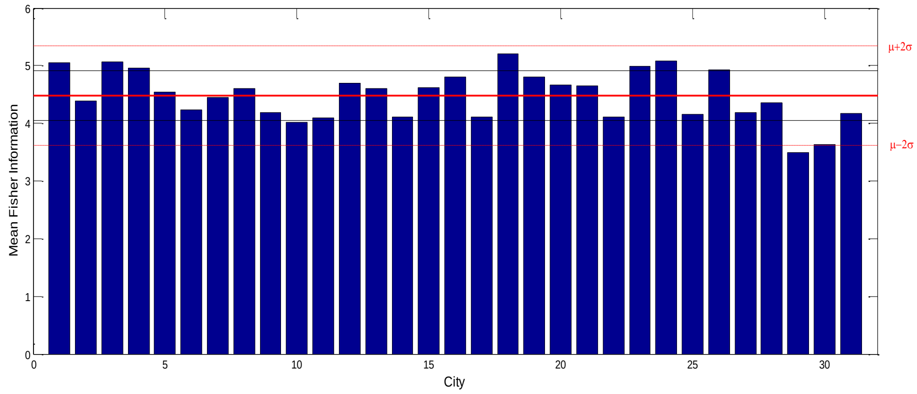
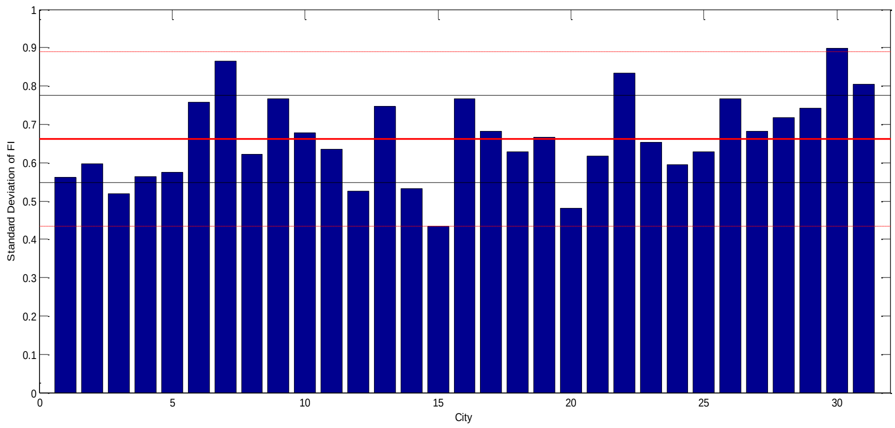


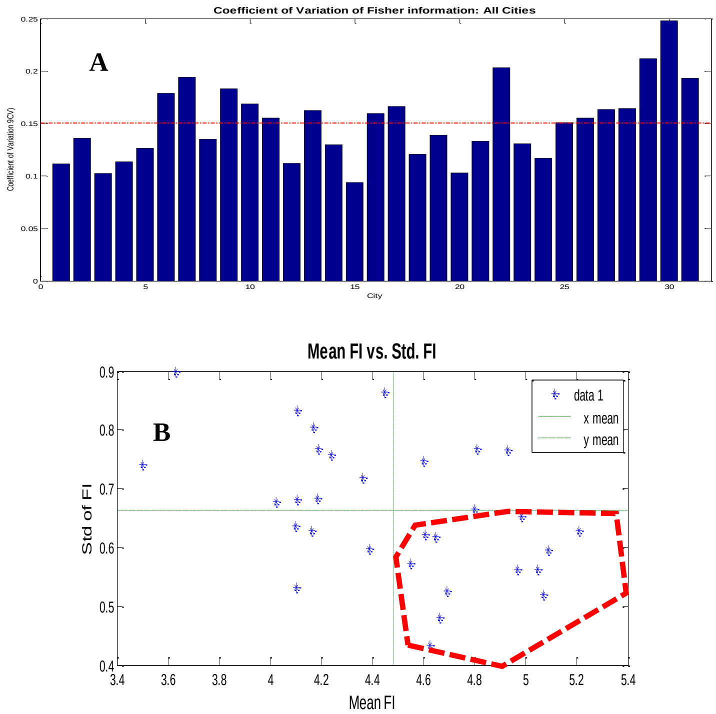
Figure 6. Standard Deviation of FI for all cities



5.1. Identifying Drivers

In order to identify the drivers of the dynamic changes in the system, the FI of the overall system (i.e., using all of the time series for each city) was compared to the FI computed from the different groupings or categories of variables. Figure 8 provides a sample plot of the FI results as computed for Alexandria, VA for the overall system and the variables separated by component (i.e., economic, climate and demographic). The Spearman Rank Order Correlation (SROC) results indicate that the economic component (rho = 0.7391) is highly correlated with the overall system. In addition, note that changes in the FI of the economic component began trending up before those changes occur in the overall system implying that economic component is a driver of the dynamic behavior of the overall system. Table 4 provides a compilation of the SROC results of the overall FI versus the FI of the components for each city. Note that the level of correlation varies from city to city. The FI of twenty-five cities had statistically significant correlations with the economic component, followed by twenty-two cities with a strong correlation with the demographic component.

Figure 7. Identifying the most resilient cities



(A) While, the coefficient of variation indicates that there are sixteen cities whose CV ratio rests below the mean CV for all cities,
(B) the μFI vs. σFI plot designates a region containing twelve cities at the intersection of both relatively high FI and low deviation.

A weighted average was used to produce an average correlation for each component within each state. From the compiled statistic, note that while the dynamic changes in Virginia, Georgia, Kentucky, and North Carolina cities are strongly related to the economic component, the behavior of the cities in South Carolina, Florida, Tennessee, Alabama and Mississippi are driven by the demographic component. In summary, the cities had a moderate correlation with both the demographic component (Educational Attainment variables: HS and College) and the economic component (HH income, poverty rate and % mfg worker). Although climate appears to be relatively unrelated to the resilience of the cities, this study focused on the southeastern United States which has a notably moderate climate. Hence, it is possible that this category plays a more important role when studying and comparing multiple geographic regions.

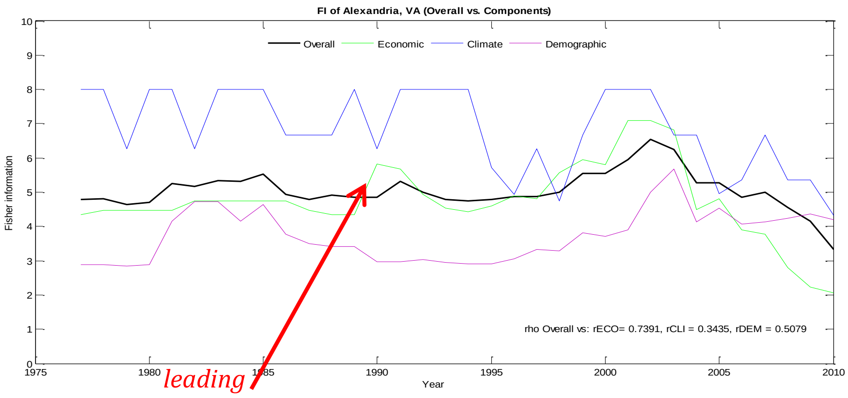
Table 4. Spearman Rank Order Correlation (SROC): Overall vs. Components

OVERALL SYSTEM							Weighted average		
State	City						ECO	CLI	DEM
Virginia	ECO (0.7391**), DEM(0.5079*)	ECO (0.6511**), DEM (0.6312**)	ECO(0.7881**), DEM(0.7915)	ECO(0.6188**), CLI(0.6477**), DEM(0.5728**)	ECO (0.8367**), CLI(0.6227**), DEM(0.8972**)		0,72676	0,25408	0,68012
Georgia	DEM(0.7912**)	ECO (0.6293**), DEM (0.6214**)	ECO(0.8202**), CLI(0.5340*)	ECO(0.6032**)	ECO(0.7366 **)	ECO (7008**), DEM (0.8129**)	0,540545	0,089	0,370917
Louisiana	ECO(0.5056*)	ECO (0.5618**), CLI (0.5273*)					0,5337	0,26365	
South Carolina	ECO(0.5096*), CLI(0.5267*), DEM(0.6359**)	ECO (0.8296**), DEM (0. 8433**)					0,6696	0,26335	0,7396
Florida	ECO(0.8551**), DEM(0.7812**)	CLI (0.6854 **), DEM (0.7940**)					0,42755	0,3427	0,7876
Kentucky	ECO(0.7709**)	DEM (0.6070**)	ECO(0.7060**), DEM(0.7886**)				0,4923		0,4652
Arkansas	CLI(0.5141*)							0,5141	
Tennessee	DEM(0.5541**)	ECO (0.4871 *)					0,24355		0,27705
Alabama	ECO(0.5790 **), DEM(0.9077**)	ECO (0.5655**), DEM (0.5582**)	DEM(0.5408**)				0,3815		0,6689
Mississipi	ECO(0.6076 **), DEM(0.8232**)	ECO (0.6222**), DEM (0.7181**)					0,6149		0,77065
North Carolina	ECO(0.7009**)	ECO (0.5066*), DEM (0.7613**)					0,60375		0,38065
West Virginia	ECO(0.7169**), DEM(0.7887**)						0,7169		0,7887
						mean	0,541005	0,287813	0,592939
						# cities	25	7	22
						%	80,65%	22,58%	70,97%

*Note: * = p-value < 0.05 and ** = p-value << 0.05.*
Each cell relates to the city denoted in the Table 1 matrix.

A similar analysis was performed to compare the FI of population to the FI of the components of the system (Table 5). From the state summary statistics of the SROC results, population is positively correlated with the demographic component (Educational Attainment variables: HS and College) and negatively correlated with the economic component (HH income, poverty rate and % mfg worker). However, note that for all of the summary SROC analysis, the direction (positive or negative) of the correlation varied by city. Such a result implies that although there are some similar patterns, the drivers of the dynamic behavior in the cities are distinct.

Figure 8. FI results for Alexandria, VA (Overall and Components)



5.2. Linking population size, growth and stability

Pumain and Moriconi-Ebrard (1997) found that major cities in some countries have grown faster than the rest of the cities in their country, a result which lends strong support to the proposition that the relationship between city size and growth is more complex than that suggested by Gibrat's law (Portnov et al., 2012). Research on metropolitan areas in the United States, further supports this position, as Gibrat's law was rejected in a time series analysis of major U.S. metropolitan areas (Black and Henderson, 2003), as does research on municipalities and contiguous urban areas in Europe (Portnov et al., 2012), cities in India (Sharma, 2003) and China (Anderson and Ge, 2005), as well as urban growth in the Balkans (Dimou and Schaffar, 2009). Additionally, a recent study found that firm growth is related to firm size and the majority of regions in Portugal (Barbosa and Eiriz, 2011).

Results of this analysis revealed that firms experience correlation of growth patterns at the regional scale as a result of differences in industrial diversity, entrepreneurship and workforce quality (Barbosa and Eiriz, 2011). In short, the results in this analysis demonstrate that geographic location matters for firm size and growth (Barbosa and Eiriz, 2011). Xu and Harriss (2010) documented a similar pattern of spatial and temporal autocorrelation in city growth rates in Texas from 1850 to 2000. Gonzalez-Val (2011) documented deviations from Zipf's law in American cities (2000), and found that most cities were larger than predicted by Zipf's, while small cities were smaller than predicted by Zipf's. Factors affecting whether the city was larger or smaller than predicted by Zipf's were per capita income, human capital and the percentage of the population employed in certain sectors (Gonzalez-Val, 2011). Further, in an analysis of the U.S. city size distribution in the 20th century, Zipf's law only held at the top of the distribution, and not for the entire city size distribution (Gonzalez-Val, 2010). Schaffar and Dimou (2012) rejected Zipf's law for the Indian city size distribution.

Table 5. Spearman Rank Order Correlation (SROC): Population vs. Components

POPULATION							Weighted average			
State	**City**						**ECO**	**CLI**	**DEM**	**NA**
Virginia	ECO(-0.3734*), DEM(-0.4006*)	DEM (0.5607**)	DEM (-0.4414*)	DEM (0.5650*)	NA		-0,07468		0,21698	
Georgia	ECO(0.5683**), DEM(-0.7773**)	NA	DEM (-0.5890**)	ECO (-0.4609*), CLI (-0.4766*)	DEM (-0.7507**)	DEM (0.3438*)	0,0179	-0,07943	-0,197367	
Louisiana	ECO(-0.4339 *)	DEM (0.5011*)					-0,21695		0,25055	
South Carolina	ECO(-0.3455*), DEM(0.3574*)	NA					-0,17275		0,1787	
Florida	NA	DEM (-0.7497**)							-0,37485	
Kentucky	NA	ECO (-0.4136*)	NA				-0,13787			
Arkansas	NA									
Tennessee	NA	ECO (-0.6914**)					-0,3457			
Alabama	CLI(0.4038*), DEM(0.5616**)	ECO (0.4887*)	ECO (-0.3503*)				-0,04613	0,1346	0,1872	
Mississipi	NA	ECO (0.7887**), DEM (-0.3763*)					0,39435		-0,18815	
North Carolina	ECO(-0.4039*), CLI(0.3484*)	ECO (0.4129*)					0,0045	0,1742		
West Virginia	ECO(0.5372*), DEM(0.6400**)						0,5372		0,64	
						mean	-0,0040	0,0765	0,0891	
						# cities	12	3	14	9
						%	38,71%	9,68%	45,16%	29,03%
						+	5	2	7	
						-	7	1	7	

*Note: * = p-value < 0.05 and ** = p-value << 0.05.*
Each cell relates to the city denoted in the Table 1 matrix.

The results of this study provided insight on the drivers of growth for cities in the southeastern United States and highlighted the fact that the drivers of stability and population growth are distinct. In an effort to further connect the key principles in this area, we compiled results to explore the relationship between population size, growth and stability. Some additional key findings are provided: (1) as city size increases, growth rates decrease (Figure 9); (2) from Figures 10 and 11, note that the majority of cities contain less than 300,000 people and there is a clear demarcation in behavior underscoring the point that as city size increases the mean FI increases. The correlation between mean FI and population size coupled with the link between increasing population size and decreasing standard deviation is an indication of increasing dynamic order and therefore, resilience for larger cities; and (3) we tested the "predictable city" theory as proposed by Bettencourt and West (2010).

Using four variables for one year and 360 cities, they found a linear relationship between increasing population size and the variables under study (crime, GDP, income, and patents) and concluded that cities of different sizes are basically scaled versions of each other and that size is the most important characteristic of a city. Using the same approach with the variables used in our study, our cities did not show this same scaling effect (Figure 12). Hence, the scaling of key variables with population growth does not appear to be a homogeneous phenomenon.

Figure 9. Mean Population vs. Growth rate from 1970 to 2010

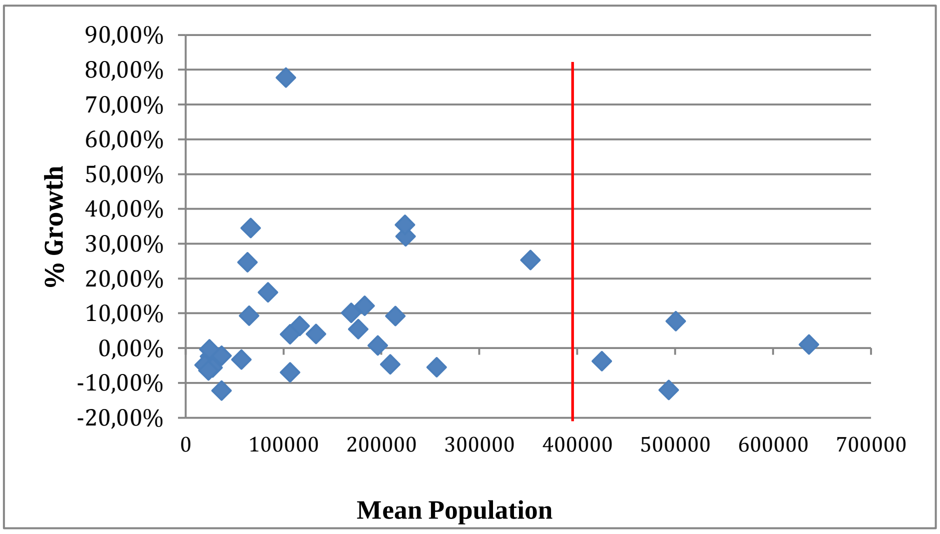


Figure 10. Mean population vs. mean FI

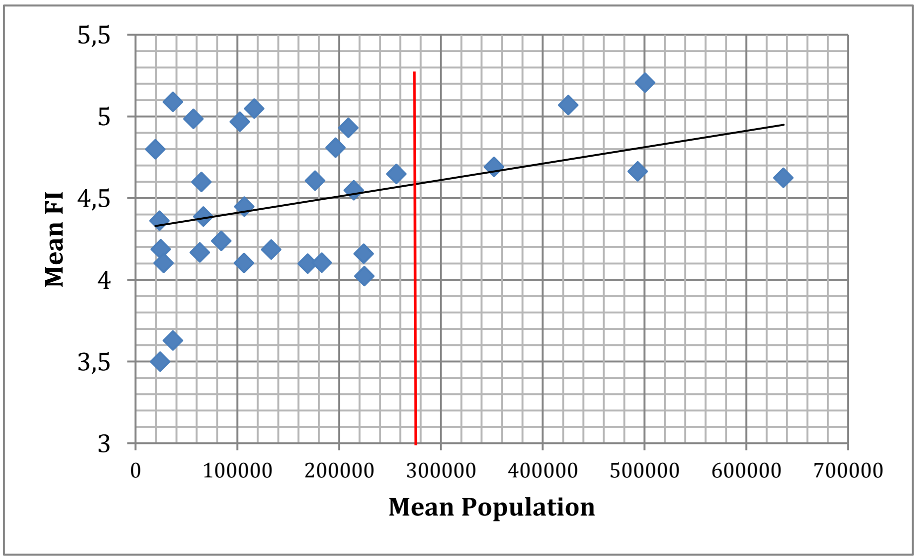


Figure 11. Mean population vs. Standard deviation of FI: Variability in the dynamic behavior of the cities tended to decrease as city size increased suggesting that the larger cities exhibited more stability

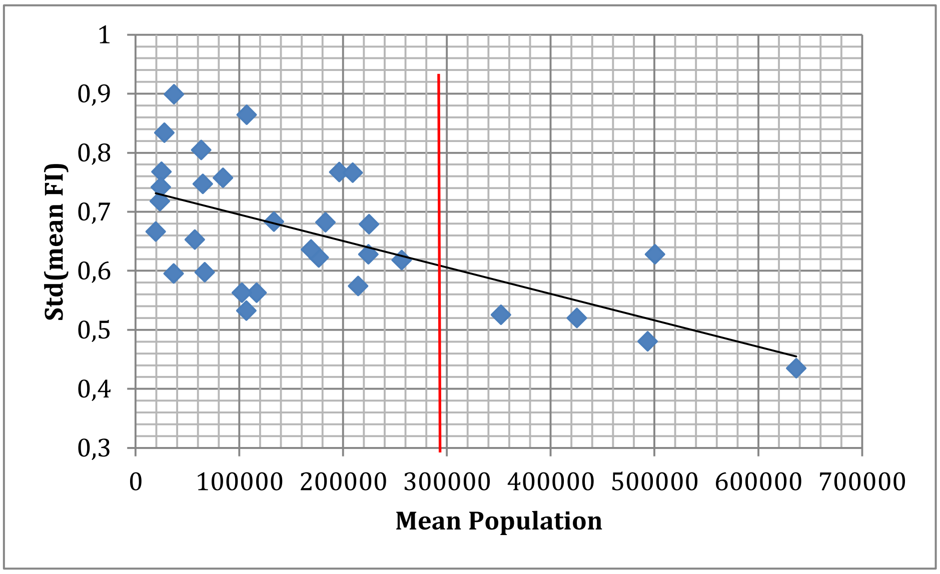
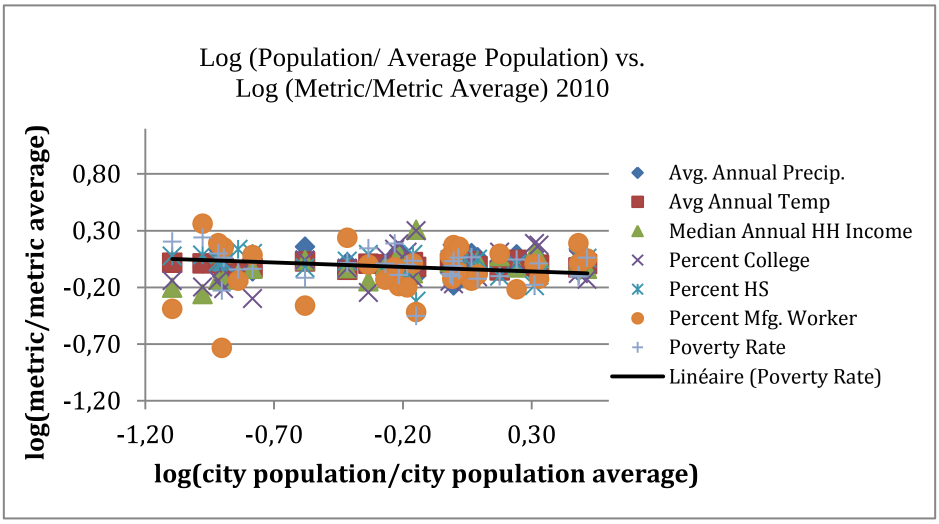


Figure 12. Scaling effect not present for study on southeastern US cities



This is possibly due to the fact that our study involved variables that although they are "peer-reviewed" and used in other studies, they are indeed different than those used by Bettencourt and West (2010). In addition, the number of cities or time period of the analysis may be important. Perhaps their assessment covers a year where the scaling effect was unambiguous prior to the many economic and social changes in the US. There truly are a number of reasons why their contention does not hold for our analysis; however, the "unified theory" is an interesting concept to investigate.

Figure 13. Summary of Positive Correlations by State

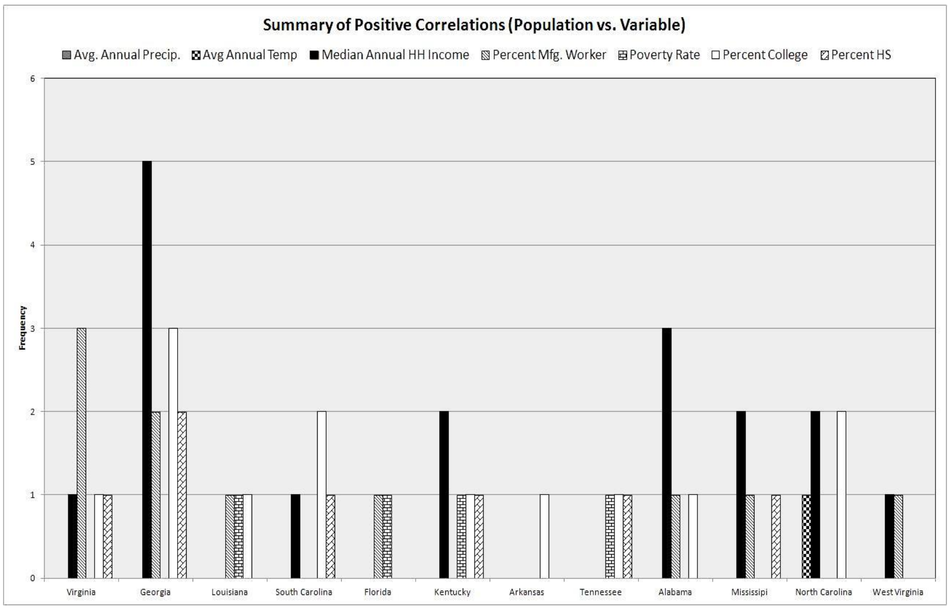
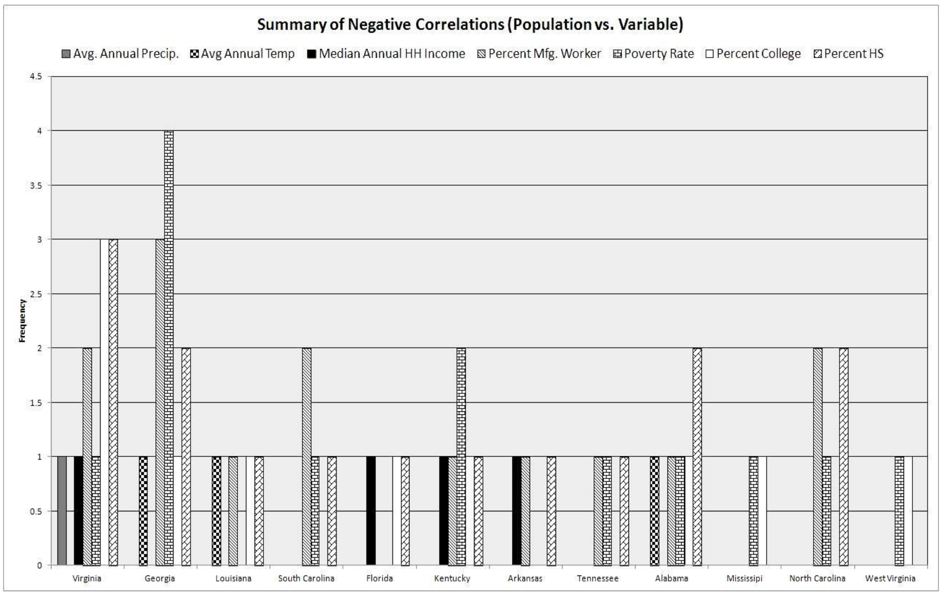


Figure 14. Summary of Negative Correlations by State



Glaeser and Shapiro (2003) found that city growth was driven by three factors: skilled labor, a warm dry climate, and reliance upon automobile-based transportation instead of public transportation. Further, skilled labor has a greater effect on growth rates in cold weather, rather than warm weather metropolitan areas in the U.S. (Glaeser, 2005). Cities with a greater proportion of skilled labor, are more resilient, and therefore have greater adaptive capacity than less skilled cities (Glaeser and Saiz, 2003). What this suggests is that specialized cities may enjoy initial success, but simply do not have as great a capacity for reinvention as cities with a more diverse economic base (Glaeser and Saiz, 2003). Importantly, size likely plays a role in this reduced adaptive capacity, in addition to the lack of skilled labor and a diverse economy (Erickcek and McKinney, 2006).

In 2001, Glaeser assessed growth and decline for nearly 200 U.S. cities from 1990 to 2000 and noted heterogeneous population growth patterns. Further, he compared the cities aggregated by percentage of growth to key variables including average daily temperature, median household income, percent of civilians involved in manufacturing employment, percent of persons who drive to work alone and percent of foreign born population. He found that higher daily temperature, high median household income, and moderate immigrant population were all characteristic of cities that grew. He also alluded to the importance of skilled labor and poverty rate in the growth and shrinkage of city populations. For our cities, we attempted to drill down into the data for each city to compile the key variables which correspond to population change by using SROC to assess the relationship between population and the variables used to characterize each city over time. Plots for each state were developed to compile the correlation results reported as the frequency in which a particular variable was noted as positively (Figure 13) or negatively (Figure 14) correlated with population. Results indicate that while median household income and percent of population with a college degree are the most frequently correlated with population growth, percent of population with a HS degree or less, percent of manufacturing workers and poverty rate are often negatively linked with population growth.

CONCLUSION

Viewing cities as a system allows for the characterization of urban systems as complex adaptive systems, which have scale-dependent structure and cross-scale dynamics, as the system of cities and their environment evolve over time (Xu and Harriss, 2010; Garmestani et al., 2009; Bessey, 2002). Favaro and Pumain (2011) suggested a model of spatially and temporally interdependent geographic entities, as an improvement upon Gibrat's model based upon independent entities. The model is based upon the idea that urban systems are the manifestation of interactions between cities and their environment. One of the key aspects of this model is that deviations from the models are not treated as anomalies or outliers, but as critical information that influences the future trajectory of the system (Favaro and Pumain, 2011). Further, the conceptual underpinnings of the model are based upon a set of innovation cycles that are partially superimposed, as cities in the system compete, adapt to change and grow.

This is remarkably similar to systems concepts from ecology, in particular Holling's adaptive cycle (Gunderson and Holling, 2002), and Odum's pulsing cycle of change (Odum, 1983; Campbell and Garmestani, 2012).

In this work, we examined the relationships between city size, growth rates, and the key factors that impact resilience and population dynamics in urban systems over time. Results of this work indicate that while there are similarities between cities, certain factors appear to be more important in one place than another, and that city growth is not random, but rather, correlated with key factors (Schaffar and Dimou, 2012). In this study, we proposed an Information theory-based approach to assessing resilience in urban systems and identified the most resilient cities. In the southeastern United States, the most resilient cities were the largest cities in the analysis, which lends further strength to the proposition that urban systems partition into levels in a dynamic hierarchy (i.e., a panarchy) (Garcia et al., 2011). We also used statistical tests to determine potential drivers of dynamic behavior in the cities and found significant correlations with the economic and demographic components in the analysis. In particular, we found that city growth was driven by mean household income and the percentage of the population of a city with a college degree.

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DYNAMIQUES CROISÉES D'UN SYSTÈME URBAIN RÉGIONAL

Résumé *- Depuis les théories des places centrales jusqu'aux travaux sur les lois de Zipf et de Gibrat, les systèmes urbains et leur hiérarchie sont l'objet d'un important courant de recherche. Plus récemment, un ensemble de travaux analyse les systèmes urbains du point de vue de la panarchie et de la résilience, en mettant en évidence le rôle des effets d'échelle. Dans ce travail, nous examinons la relation entre la taille des villes, leur taux de croissance démographique et les facteurs explicatifs des dynamiques démographiques d'un système urbain régional. Les résultats montrent que la croissance urbaine n'est pas un processus aléatoire mais un processus déterminé par certains facteurs fondamentaux, pas nécessairement les mêmes pour chaque ville. Parmi ces facteurs, on trouve le niveau de revenu des ménages et la part de la population ayant un diplôme universitaire.*

Mots-clés : SYSTÈME URBAIN RÉGIONAL, CROISSANCE URBAINE, DISTRIBUTIONS RANG-TAILLE, THÉORIE DE L'INFORMATION