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US MSA PCPI Trends: Evidence on Convergence and Divergence

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Abstract

Recent literature suggests that whether you observe state level convergence or divergence in PCPI depends largely on whether period beginning or ending quintile income groupings are used. The prior literature demonstrates that state income distributions based upon 1969 quintiles indicate PCPI convergence, while 2012 quintiles generate the opposite result. Evidence presented in this paper confirms similar patterns through 2017 confirming that previous results are more than recession driven anomalies. We also find considerable variability within MSA rankings over the 1969-2017 time period, a finding which suggests that MSA income performance is considerably more complex than superstar city paradigms would predict.

Keywords

income inequality, income convergence, PCPI

1. Introduction

Theoretical support for convergence of per capita income across economies dates to the work of Ramsey (1928), Solow (1956) and Cass (1965). Solow's model attributes convergence to inter-country differences in capital formation funded solely from domestic savings. International economists offer a different rationale focusing on the exchange of goods and services, ideas and factors of production to foster convergence (Slaughter, 1997). Supporting evidence for the importance of trade can be found from instances in which convergence followed liberalized trade policies (Ben-David, 1993), among countries with histories of relative openness (Sachs & Warner, 1995) or between countries with historically high trade volumes (Ben-David, 1996). Evidence regarding the importance of trade raises obvious questions regarding the potential for convergence of income within a country including among the various U.S. states. Barro and Sala-i-Martin (1992) were among the first to investigate the potential for convergence at the U.S. state level. Employing a Solow growth model, Barro and Sala-i-Martin find clear evidence of state level convergence in both per capita personal income and gross state product over the period 1840-1988. Subsequent studies by Levernier, Partridge, and Rickman (1995), and Bernat (2001) offer evidence of state level convergence of PCPI through 1990.

More recent evidence points to changes in PCPI convergence trends across US states and regions (Crain, 2003; Berry & Glaeser, 2005; DiCecio & Glascon, 2010). Ganong and Shoag (2017) report convergent rates for the period 1990-2010 at roughly half the US historical norm with virtually no convergence occurring in the period immediately prior to the Great Recession. Using data covering 1929-2005, Fousekis (2007) finds large number of states that did not converge to the national average per capita income. Using a time series approach, Kane (2001) concludes that different regions experienced convergence across different time periods. Similarly, Connaughton and Swartz (2015) conclude that the question of convergence depends upon the selection of initial state grouping. When states are grouped by 1950 PCPI quintiles, the results are consistent with convergence. However, using 2012 PCPI quintiles generates patterns more consistent with divergence of state PCPI.

Recent literature suggests that changing migration patterns could explain changes in convergence patterns. Evidence points to recent declines in interstate migration (Kaplan & Schulhofer-Wohl, 2017; Molloy, Smith, & Wozniak, 2014**)** as an important factor that may contribute to the recent lack of PCPI convergence. The recent lack of state level PCPI convergence occurs at a time when the issue of growing income inequality among individuals has gained attention in the media, in academia, and in government. In the U.S., the share of income received by the top 10% increased from 30 percent in 1980 to 48 percent in 2014. At the same time, the share of income of the top 1 percent increased from 8 percent of total income to 19 percent (IMF, 2014). Juxtaposing this trend with the dynamic behavior of MSA PCPI discussed in this paper gives rise to myriad questions about future trends in income distribution at both the state and individual levels.

This paper examines the diverging trend in MSA PCPI and compares developments in recent years to convergence findings from previous studies. We also analyze changes in the trend and offer explanations for why these changes are occurring. Both variable factors (economic structure, density) and fixed factors (geographic location) affecting MSA PCPI rankings are addressed as contributing to this trend. In light of recent concerns over income inequality and the income gap between rich and poor growing, the analysis presented in this paper will provide additional insight into understanding how changes in PCPI and PCPI rankings over time are influenced.

The Bureau of Economic Analysis (BEA) maintains regional economic data for MSAs dating to 1969.Annual Income, earnings, and employment by Industry are available on an annual basis by MSA from 1969 to 2017 (Tables CA1-3, CA04, CA25, and CA25N). These series provide a wealth of information for comparing economic activity across MSAs and examining changes in MSA data over time. This paper will focus on MSA per Capita Personal Income (PCPI) over the 44 year period and identify trends in MSA PCPI over time and changes in PCPI rank and position among MSAs.

2. Literature Review

There is a rich and growing body of research testing the conclusions of growth theory's forecast of income convergence. Previous research defines convergence in alternative ways, ranging from β-convergence and σ-convergence to measures such as Gini coefficients and ratios of mean or median income at specific benchmark points in the distribution. Techniques are similarly wide-ranging including OLS, 2- and 3-stage least squares, transition matrices, spatial clustering, unit root tests, and more.

The essential finding is that there are periods of income convergence interrupted by periods of mixed results and general divergence. The earliest work by Barro and Sala-i-Martin (1992) and Mankiw et al. (1992) found evidence of convergence. Research by Levernier, Partridge, and Rickman (1995), and Bernat (2001) established the convergence of PCPI among the states through 1990.Convergence evidence is sufficiently well established that Sala-i-Martin (1996) concluded "we can use a mnemonic rule:economies converge at a speed of two percent per year".

Slowing convergence and divergence in income are generally found in the late 1970s and 1980s and again more recently. Yamamoto (2003) identified several stylized facts concerning income disparity by using a multi-channel analysis, including non-parametric, σ-convergence, mobility tests, and spatial clustering analysis. The paper shows higher mobility in the 1970s and 1980s, with lower, but stable, mobility levels throughout the 1990s. Furthermore, spatial clustering techniques indicate that, at smaller scales, the regional income distribution has increasingly become more fragmented. Ganong and Shoad (2014) attribute the slowing of regional income convergence since 1980 to a reduction in labor mobility. They trace the decline in labor mobility to land use regulations and high housing prices in wealthier areas. Rey and Montouri (1999) use spatial econometric methods to examine US regional economic income convergence from 1929-1994. They find strong geographic characteristics of convergence that further complicate the dynamics of income convergence across states and within state clusters. Bauer et al. (2012) use data from 1939 to 2004 to explain the late 1970s slowing of convergence to a variety of factors including: number of patents issued, college attainment as well as climate and industry structure.

DiCecio and Gascon (2010) examine convergence across states, metropolitan areas, and non-metropolitan areas in the United States. They find states that are losing positions in the income distribution are also losing population. In addition they suggest that, although there is no convergence across states or metro/no metro areas, there appears to be convergence in the personal income distribution due to population mobility. Diego Romero-Avila (2012) apply a panel stationary test to examine stochastic properties of U.S. state income levels over the 1929-2004 period. The intended outcome of this test is to determine whether U.S. state personal income series follows a stochastic trend or is trend stationary. They find evidence of "regime-wise stationarity" in U.S. state personal income during the twentieth century. Christopoulos and Tsionas (2007) allow output convergence to follow a non-linear process. They use the logarithm of regional aggregated real per capita personal income over the 1929-2001 period. Hristopoulos and Tsionasdetect stochastic convergence for seven out of eight BEA regions with the plains region being the lone exception.

Holmes et al. (2014) use data from 1929 to 2009 to test for convergence using unit root and non-co integration tests. They find convergence in that forecasts of state incomes are proportional rather than equal. When applied to MSA data for 1969-2012, their approach provides stronger convergence effects than measures obtained using conventional techniques.

While convergence is often considered across states or within regions, an examination of a smaller unit (Metropolitan Statistical Areas (MSAs), cities, or counties) is valuable because these units more closely approximate an integrated economic zone. Drennan et al. (1996) examine divergence of median family incomes in the 1980s for the 51 largest US cities and find that cities with a high share of earnings from producer services have higher economic growth rates than cities that began the decade with a higher concentration of earnings from manufacturing. Drennan (2005) looked at changes in wage levels in metropolitan areas for 1969-1979 and for 1979-1999. He finds that large metropolitan areas had stronger wage growth in the later period. The ratio of earnings from producer services to earnings from production and distribution also supported higher wage growth in the later years.

Higgins et al. (2006) use county-level data to study convergence rates. They find that public sector employment at any level has a negative effect on economic growth. Education contributes to growth with the largest contributions coming from completed high school and completed college or higher. Employment in the finance, insurance, and real estate and entertainment industries add to economic growth while employment in education exerts a negative impact. Hammond and Thompson (2006) examine both convergence to the trend (modality) and mobility within groups in their study of metropolitan and nonmetropolitan regions from 1969 to 1999.Their analysis of sub-state units produces higher rates of distributional and rank mobility than state analysis indicated. They find that mobility across income classes is lower in metropolitan areas than for nonmetropolitan zones and that the metropolitan areas have lower mobility across ranks.

3. Data

This study uses PCPI for each of the 383 Metropolitan Statistical Areas (MSAs) listed by the Bureau of Economic Analysis. The BEA maintains responsibility for the backward compatibility of the data series as MSAs expand or are added to the series. The data cover 1969 through 2017 for a total of 49 years of observations. Factors affecting the MSA PCPI include the presence of research universities in the MSA, industry composition, the MSA population density, and the BEA region in which the MSA is located. Data on the presence of a top 200 research university in the MSA were obtained from the *US News and World Report* ranking of universities for 2012.Data on population and employment by industry for each MSA were also sourced from the BEA.

4. Findings

4.1 PCPI and Convergence

MSA PCPI data exhibit substantial variability over the study period as shown by the summary statistics in Table 1.The ratio of the maximum PCPI to the minimum reflects changes in the spread of the distribution. In 1969, the highest PCPI for an MSA was 3.4190 times the PCPI of the minimum. By 2017, this ratio increased to 4.2980.

Figure 1 shows that the beginning and ending values for the ratio of maximum PCPI to minimum PCPI exhibit substantial variation. The peaks are periods when the maximum PCPI rose relative to the minimum and the troughs are years when the minimum increased relative to the maximum. The trend for the period is upward suggesting the highest income MSA gained relative to the lowest income area.

To investigate the variability of the PCPI data further, MSAs were divided into quintiles according to their starting PCPI values and then again according to their ending values. The distribution of MSAs by BEA region is shown in Table 2.

Figure 2 shows the relative PCPI for the MSAs in each quintile where relative PCPI is the average PCPI for the quintile divided by the average PCPI for all 383 MSAs.

Table 1. PCPI Summary Statistics for MSAs, 1969-2017

Item	1969	2017
Average PCPI	$3,574	$45,693
Standard Deviation	608.7	9,435.6
Minimum	$1,809	$25,617
Maximum	$6,184	$110,104
Maximum/Minimum	3.4190	4.2980

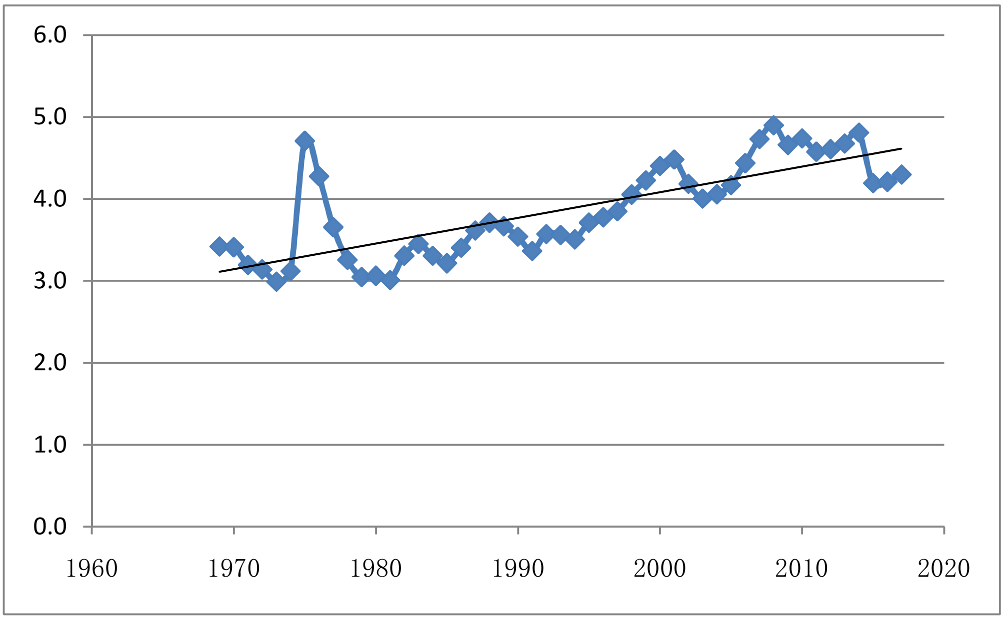

Figure 1. MSA Maximum PCPI / Minimum PCPI 1969-2017

Table 2. 1969 Quintiles by Region

1969 Quintiles	Top Quintile	2nd	3rd	4th	Bottom Quintile	Region Total
New England	8	4	2	0	1	15
	53%	27%	13%	0%	7%	
Mideast	9	14	8	7	3	41
	23%	35%	20%	18%	8%	
Great Lakes	16	25	12	4	2	59
	27%	42%	20%	7%	3%	
Plains	7	5	8	9	4	33
	21%	15%	24%	27%	12%	
Southeast	6	9	20	31	54	120
	5%	8%	17%	26%	45%	
Southwest	3	8	7	14	8	40
	7%	20%	17%	34%	20%	
Rocky Mountains	4	2	6	8	3	23
	17%	9%	26%	35%	13%	
Far West	24	10	14	4	0	52
	46%	19%	27%	8%	0%	

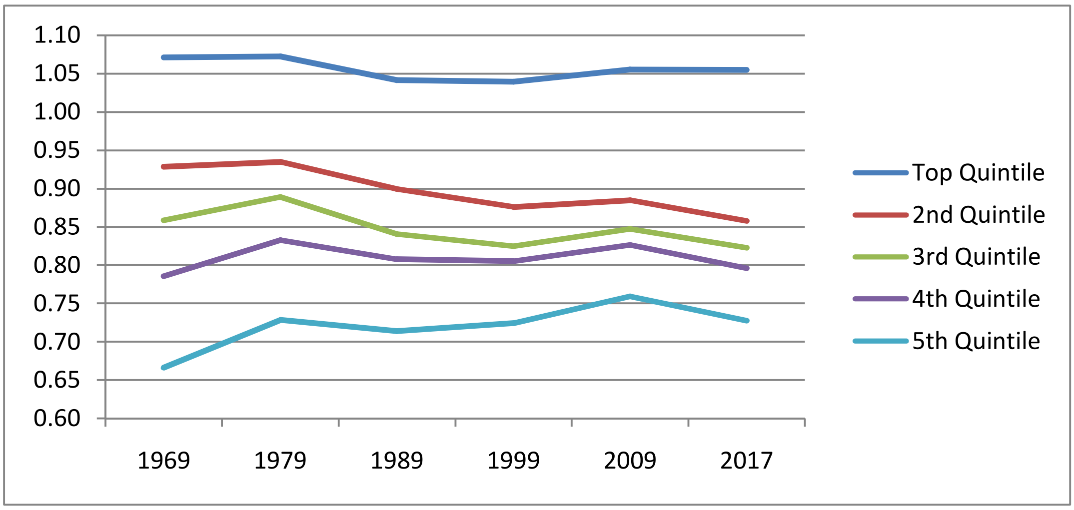

Figure 2. Relative PCPI by 1969 Quintile Ranking 1969-2017

The top quintile experiences a small loss in relative income in the early years of the period, but thereafter remains at least 20% above the average for all MSAs. The second and third quintiles experience some loss in relative position and the lowest two quintiles experience gains over the period.

The process of identifying and tracking quintiles was repeated using 2017 income. The regional distribution is shown in Table 3. A comparison of Tables 2 and 3 shows that some regions gained in relative income while others lost. In New England, the number of MSAs in the top quintile increased from 8 in 1969 to 12 in 2017.Similar gains were seen in the Southeast, and in the Southwest. MSAs in the Great Lakes and Rocky Mountain regions moved down the quintile rankings while MSAs in the Mideast and Plains showed experienced stable results.

Figure 3 shows relative PCPI by 2017 quintile ranking. This allows us to track the origins of MSAs based on their 2017 quintile PCPI. The top quintile experienced gains in income, starting 7.6% above the average and ending with a PCPI that is 15.8% above. The other four quintiles experienced losses with the decline being most pronounced for the lowest income group in 2017. The MSAs in the bottom quintile were 77.5% of average income in 1969 and they fell to 70.4% of average by 2017. Income increases for the top quintile with reductions in the four remaining quintiles provide evidence of increasing divergence as opposed to income convergence. Our results establish that the pattern of income divergence revealed by Connaught on and Swartz (2015) using 2012 quintiles extends through 2017. While an argument could be made that 2012 data with year's end unemployment of 7.9% were heavily influenced by the aftermath of the recession, the end of year unemployment rate at 4.1% for 2017 indicates economic activity approximating potential GDP. In short, our results establish that the previous finding is not merely the end result of labor market disruptions due to the after effects of a severe economic downturn.

Table 3. 2017 Quintiles by Region

2017 Quintile	Top Quintile	2nd	3rd	4th	Bottom Quintile	Region Total
New England	12	1	0	2	0	15
	80%	7%	0%	13%	0%	
Mideast	10	12	11	6	2	40
	25%	30%	28%	15%	5%	
Great Lakes	8	20	10	12	9	59
	14%	34%	17%	20%	15%	
Plains	7	10	8	6	2	33
	21%	30%	24%	18%	6%	
Southeast	11	16	23	29	41	120
	9%	13%	19%	24%	34%	
Southwest	6	4	8	12	10	41
	15%	10%	20%	29%	24%	
Rocky Mountains	3	7	5	2	6	23
	13%	30%	22%	9%	26%	
Far West	20	7	12	8	5	52
	38%	13%	23%	15%	10%	

As we have already seen in Tables 2 and 3, MSA income growth varied by region. Figures 4A through 4H chart the PCPI for the MSAs in that region.

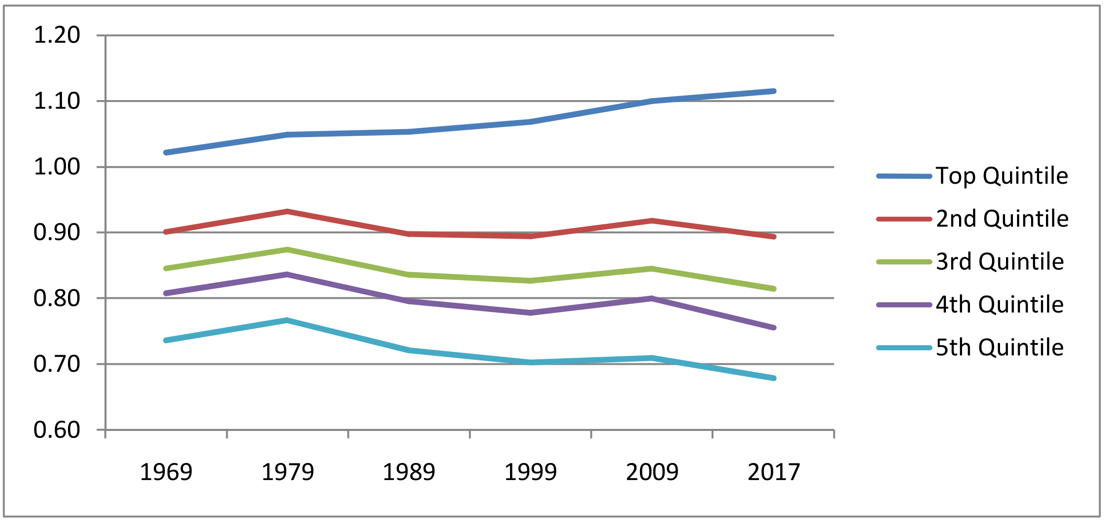

Figure 3. Relative PCPI by 2017 Ranking 1969-2017

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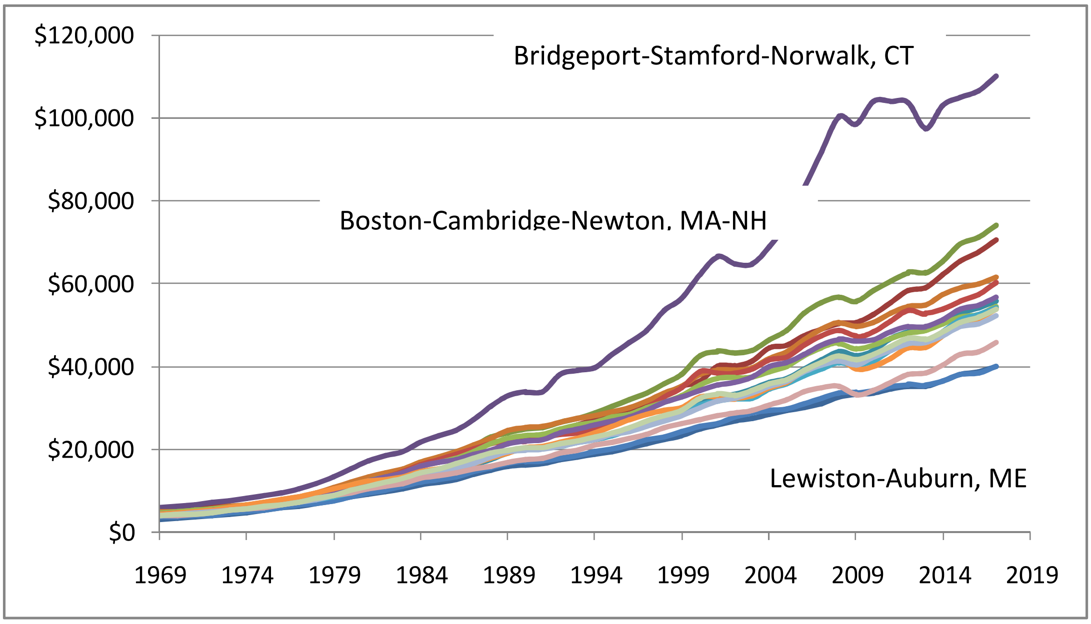

Figure 4A. Region 1: New England N = 15

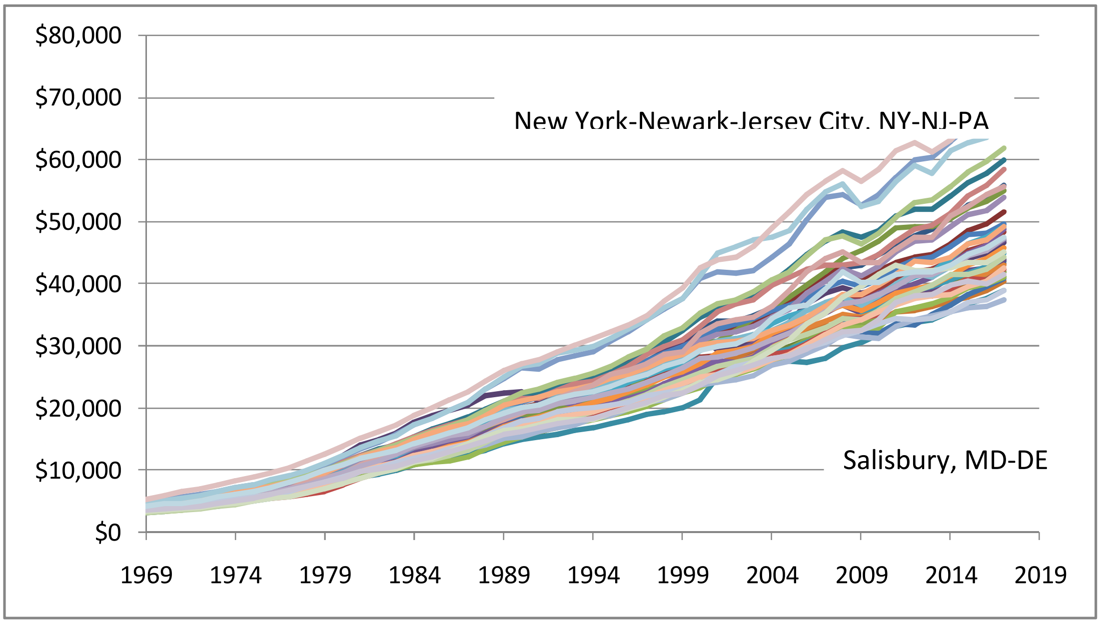

Figure 4B. Region 2: Mideast N = 4

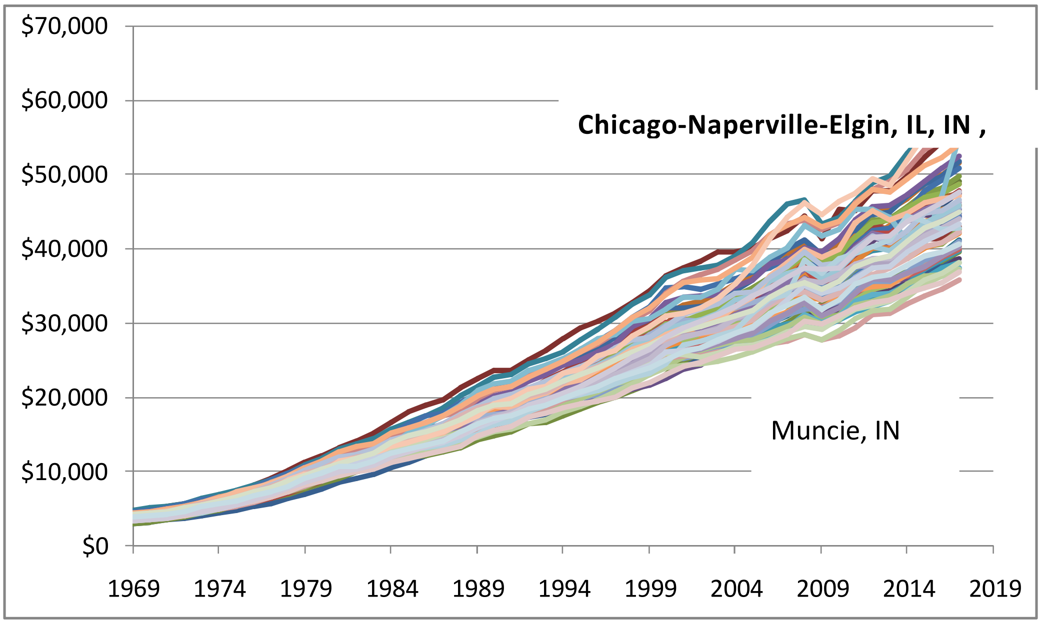

Figure 4C. Region 3: Great Lakes N = 59

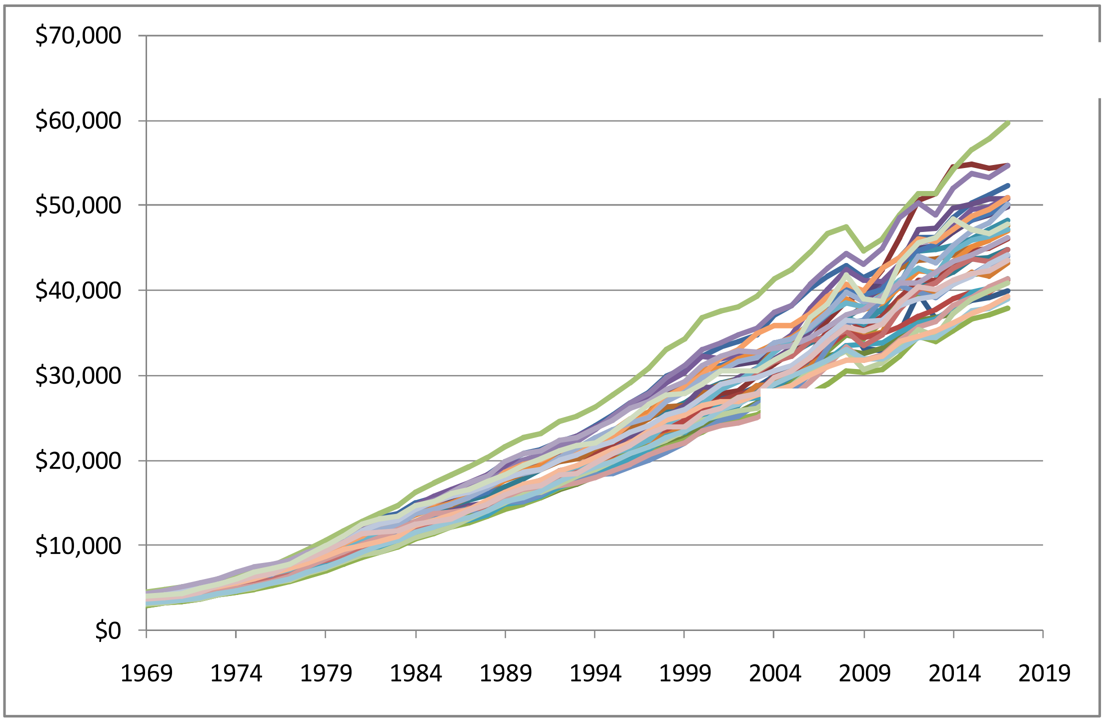

Figure 4D. Region 4: Midwest N = 33

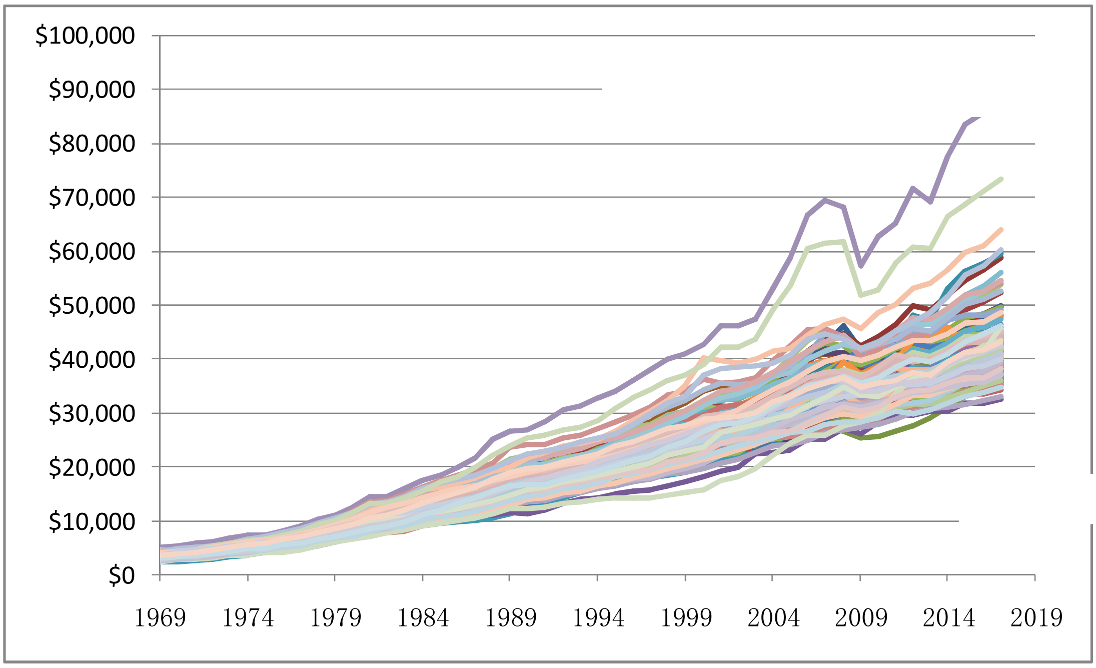

Figure 4E. Region 5: Southeast N = 120

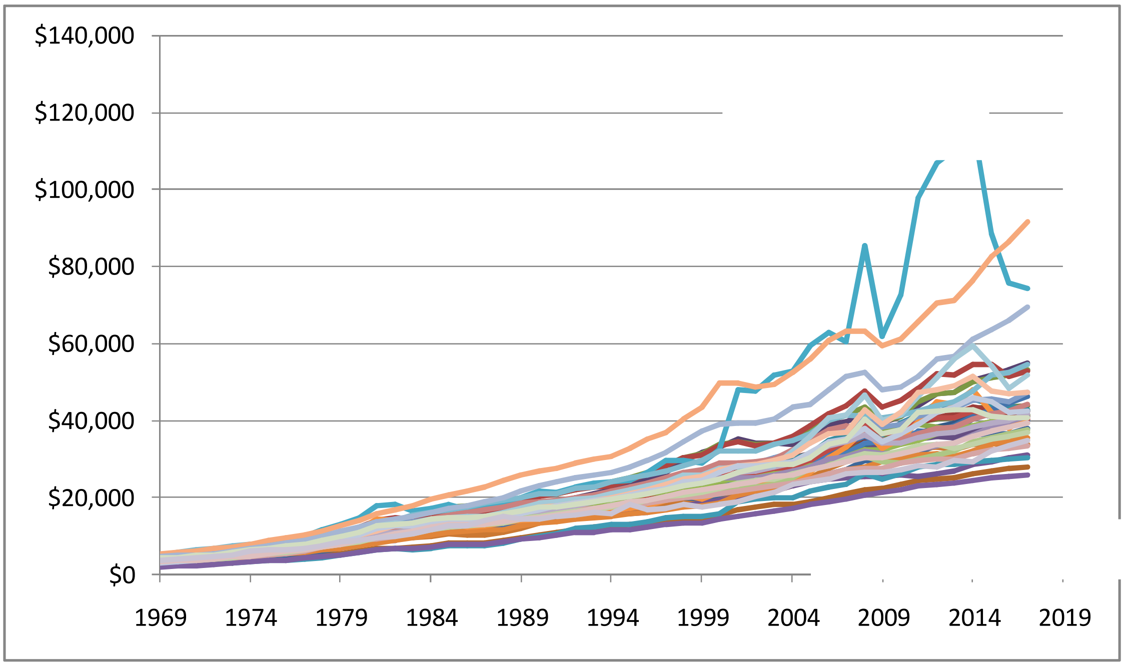

Figure 4F. Region 6: Southwest N = 40

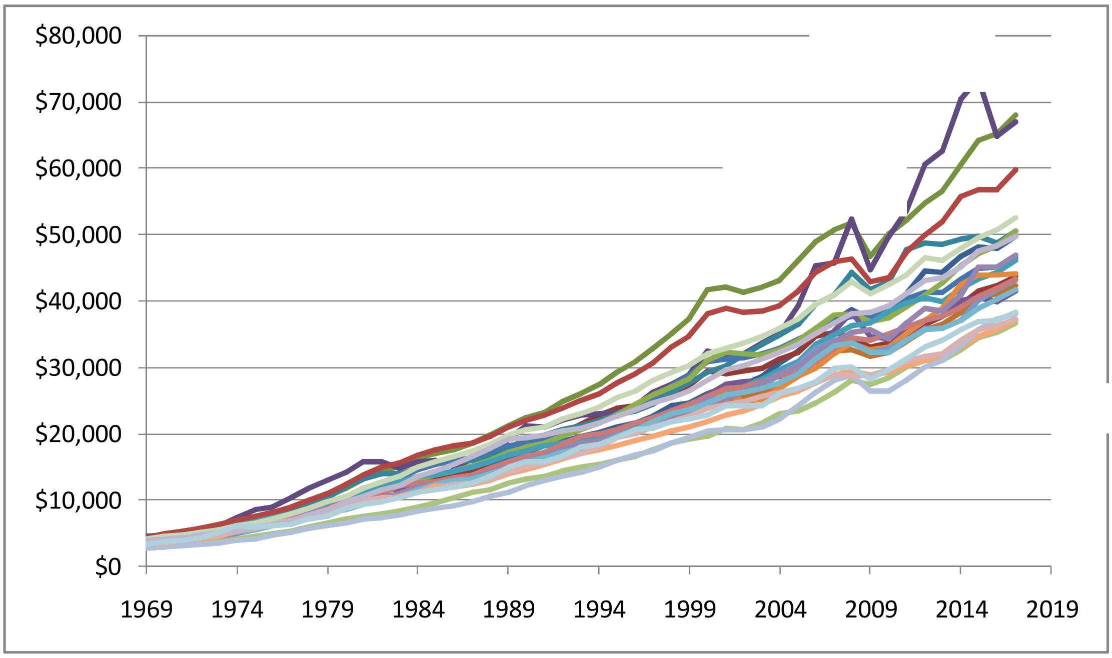

Figure 4G. Region 7: Rocky Mountains N = 23

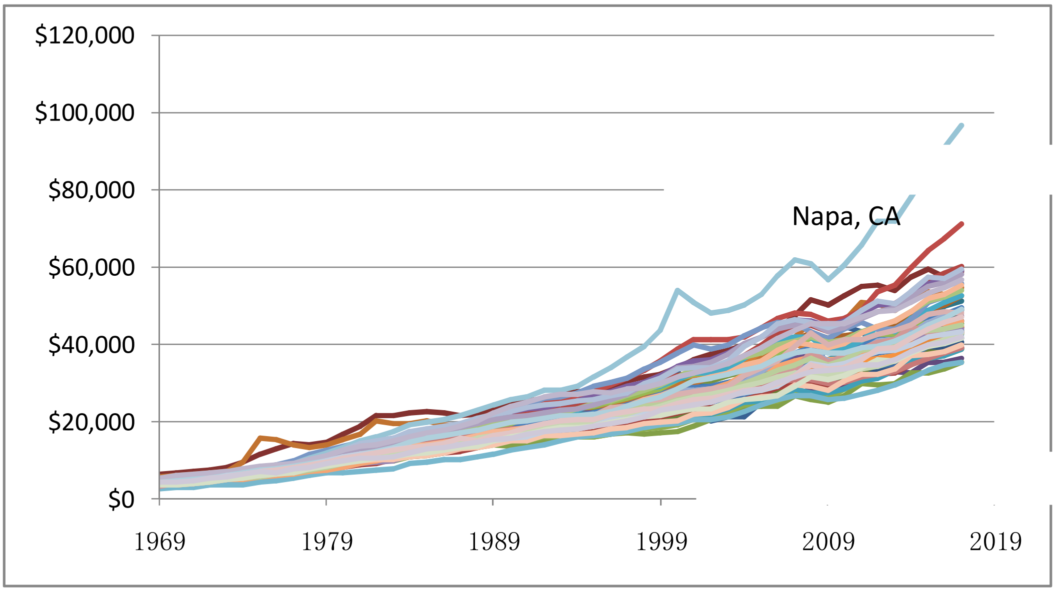

Figure 4H. Region 8: Far West N = 52

4.2 MSA Rank

Given the disparate experiences of MSAs and the seeming lack of consistent income convergence, analysis of the mobility of MSAs is the next logical step. Hammond and Thompson (2006) argue, "… sustained inequality in the income distribution may cause us less concern if we also find a large degree of income class and rank mobility." (p. 36).

Table 4. Changes in Rank for MSAs1969 – 2017

1969 Rank Minus2017 Rank	Positive	Negative
1-49	98	83
50-99	49	50
100-149	31	20
150-199	17	18
200-249	1	11
250+	2	0

The remainder of this paper examines change between the 1969 rank and 2017 rank. These data show some large changes among some MSAs with most MSAs experiencing more moderate changes. Table 4 shows a frequency distribution of both the gains in rank (positive changes) and the loss in rank (negative changes). Three MSAs had no rank change.

Table 5A lists the MSAs with the largest positive changes in rank while Table 5 B lists MSAs with the largest negative changes. Table 6A presents the top 25 MSAs by PCPI for 2017. It also shows the percentage of U.S. PCPI for each MSA. There are four MSAs that have PCPIs more than 50 percent above the U.S. average and one (Bridgeport-Stamford-Norwalk, CT) that is more than double the U.S. average.

Table 6B presents the bottom 25 MSAs by PCPI for 2017. It also shows the percentage of U.S. PCPI for each MSA. There are four MSAs that have PCPIs of less than 60 percent of the U.S. average in 2017.In addition the three lowest PCPI MSAs (McAllen-Edinburg-Mission, TX, Brownsville-Harlingen, TX, and Laredo, TX) were also the bottom three MSAs in 1969.

Table 5. AMSAs with the Largest Positive Change in PCPI Rank 1969-2017

MSA	State	Region	Change in Rank
Fayetteville-Springdale-Rogers, AR-MO	AR	5	338
Charlottesville, VA	VA	5	257
Bismarck, ND	ND	4	231
Austin-Round Rock, TX	TX	6	197
Santa Fe, NM	NM	6	192
The Villages, FL	FL	5	183
Nashville-Davidson--Murfreesboro--Franklin, TN	TN	5	182
Lake Charles, LA	LA	5	180
Winchester, VA-WV	VA	5	177
Birmingham-Hoover, AL	AL	5	176
Durham-Chapel Hill, NC	NC	5	175
Flagstaff, AZ	AZ	6	172
Wausau, WI	WI	3	172
Daphne-Fairhope-Foley, AL	AL	5	166
Sioux Falls, SD	SD	4	166
Fort Collins, CO	CO	7	164
Baton Rouge, LA	LA	5	160
Grand Forks, ND-MN	ND	4	157
St. Cloud, MN	MN	4	154
Burlington-South Burlington, VT	VT	1	152
State College, PA	PA	2	149
Knoxville, TN	TN	5	147
Raleigh, NC	NC	5	145
Alexandria, LA	LA	5	135
Tallahassee, FL	FL	5	135

Table 5. BMSAs with the Largest Negative Change in PCPI Rank 1969-2017

MSA	State	Region	Change in Rank
El Centro, CA	CA	8	-245
Lake Havasu City-Kingman, AZ	AZ	6	-236
Jackson, MI	MI	3	-235
Fayetteville, NC	NC	5	-233
Elizabethtown-Fort Knox, KY	KY	5	-232
Flint, MI	MI	3	-228
Battle Creek, MI	MI	3	-218
Bakersfield, CA	CA	8	-217
Wichita Falls, TX	TX	6	-209
Riverside-San Bernardino-Ontario, CA	CA	8	-207
Hanford-Corcoran, CA	CA	8	-201
Mansfield, OH	OH	3	-199
Sierra Vista-Douglas, AZ	AZ	6	-196
Merced, CA	CA	8	-195
Kokomo, IN	IN	3	-190
East Stroudsburg, PA	PA	2	-182
Killeen-Temple, TX	TX	6	-182
Danville, IL	IL	3	-180
Lansing-East Lansing, MI	MI	3	-175
Rockford, IL	IL	3	-174
Springfield, OH	OH	3	-174
Yuba City, CA	CA	8	-171
Palm Bay-Melbourne-Titusville, FL	FL	5	-166
Yuma, AZ	AZ	6	-166
Saginaw, MI	MI	3	-165

Table 6A. Top 25 PCPI MSAs 2017

Rank	MSA	1969	1979	1989	1999	2009	2017	Percent of U.S. 2017
	United States (Metropolitan Portion)	$4,141	$9,635	$19,583	$30,025	$40,764	$53,617	
1	Bridgeport-Stamford-Norwalk, CT	$5,885	$13,109	$32,766	$56,436	$98,364	$110,104	205.35%
2	San Jose-Sunnyvale-Santa Clara, CA	$4,875	$11,771	$24,263	$43,688	$56,482	$96,623	180.21%
3	San Francisco-Oakland-Hayward, CA	$5,323	$12,470	$25,599	$43,465	$59,442	$91,459	170.58%
4	Naples-Immokalee-Marco Island, FL	$4,949	$10,902	$26,659	$40,908	$57,289	$87,829	163.81%
5	Midland, TX	$4,403	$12,978	$19,867	$28,707	$61,554	$74,072	138.15%
6	Boston-Cambridge-Newton, MA-NH	$4,453	$9,852	$23,989	$38,111	$55,581	$74,024	138.06%
7	Sebastian-Vero Beach, FL	$3,707	$9,948	$23,781	$36,992	$51,762	$73,274	136.66%
8	Napa, CA	$4,662	$10,687	$22,235	$35,507	$46,111	$71,174	132.75%
9	New York-Newark-Jersey City, NY-NJ-PA	$4,935	$10,679	$24,775	$37,634	$52,552	$71,019	132.46%
10	Barnstable Town, MA	$4,406	$9,730	$21,918	$35,255	$50,527	$70,430	131.36%
11	Washington-Arlington-Alexandria,	$5,250	$12,368	$25,889	$39,358	$56,433	$69,581	129.77%
12	Seattle-Tacoma-Bellevue, WA	$4,660	$11,113	$21,433	$36,952	$48,025	$69,214	129.09%
13	Boulder, CO*	$4,157	$10,469	$21,212	$37,151	$46,715	$68,027	126.88%
14	Casper, WY	$4,366	$12,927	$19,084	$28,760	$44,731	$67,023	125.00%
15	Trenton, NJ	$4,475	$10,899	$25,000	$37,475	$52,448	$66,343	123.74%
16	Santa Cruz-Watsonville, CA	$4,1	$9,98	$19,8	$34,9	$45,4	$64,02	119.42%

		63	4	36	61	85	8	
17	Philadelphia-Camden-Wilmington ,	$4,334	$9,819	$21,086	$32,754	$46,385	$61,879	115.41%
18	Hartford-West Hartford-East Hartford, CT	$4,736	$10,531	$24,409	$35,050	$49,609	$61,353	114.43%
19	Santa Rosa, CA	$4,298	$10,427	$21,171	$32,991	$41,834	$60,286	112.44%
20	Los Angeles-Long Beach-Anaheim, CA	$4,820	$10,991	$20,933	$30,183	$43,025	$60,087	112.07%
21	Manchester-Nashua, NH	$4,111	$9,595	$21,986	$34,654	$47,179	$60,064	112.02%
22	Baltimore-Columbia-Towson, MD	$4,178	$9,937	$21,053	$32,305	$47,420	$59,797	111.53%
23	Minneapolis-St. Paul-Bloomington, MN-WI	$4,429	$10,547	$21,550	$34,232	$44,593	$59,736	111.41%
24	Denver-Aurora-Lakewood, CO*	$4,315	$10,866	$20,965	$34,679	$42,895	$59,660	111.27%
25	Santa Maria-Santa Barbara, CA	$4,738	$11,218	$21,949	$31,126	$44,231	$59,460	110.90%

Table 6B

Rank	**MSA**	**1969**	**1979**	**1989**	**1999**	**2009**	**2017**	**Percent of U.S. 2017**
	United States (Metropolitan Portion)	$4,141	$9,635	$19,583	$30,025	$40,764	$53,617	
383	McAllen-Edinburg-Mission, TX	$1,809	$4,817	$8,936	$13,354	$21,112	$25,617	47.78%
382	Brownsville-Harlingen, TX	$2,027	$5,235	$9,280	$14,572	$22,200	$27,741	51.74%
381	Laredo, TX	$2,161	$4,868	$8,967	$14,907	$24,514	$30,008	55.97%
380	Lake Havasu City-Kingman, AZ	$3,742	$7,676	$14,458	$18,260	$25,327	$30,865	57.57%
379	Hinesville, GA	$2,946	$7,856	$11,429	$17,166	$26,173	$32,425	60.48%
378	Pine Bluff, AR	$2,585	$6,861	$12,641	$18,909	$27,247	$32,942	61.44%
377	Sebring, FL	$3,329	$7,604	$16,109	$20,052	$27,424	$33,446	62.38%
376	Farmington, NM	$2,656	$7,647	$11,672	$18,210	$30,150	$33,751	62.95%
375	Lakeland-Winter Haven, FL	$3,255	$8,032	$15,701	$23,466	$28,777	$34,213	63.81%
374	El Paso, TX	$3,117	$6,394	$12,106	$18,071	$26,456	$34,575	64.49%
373	Valdosta, GA	$2,873	$6,641	$13,790	$21,019	$28,292	$34,739	64.79%

372	Yuma, AZ*	$3,503	$8,419	$14,254	$17,430	$26,358	$34,752	64.82%
371	Jonesboro, AR	$2,578	$6,931	$13,173	$20,813	$28,422	$35,005	65.29%
370	Dalton, GA	$3,205	$7,512	$15,570	$22,976	$25,248	$35,118	65.50%
369	St. George, UT	$2,622	$6,490	$11,462	$18,904	$25,549	$35,161	65.58%
368	Morristown, TN	$2,689	$6,309	$13,729	$22,064	$27,880	$35,263	65.77%
367	Hanford-Corcoran, CA	$3,668	$9,304	$13,843	$16,975	$24,809	$35,326	65.89%
366	Las Cruces, NM	$3,082	$6,630	$12,508	$17,639	$28,961	$35,362	65.95%
365	Bowling Green, KY	$2,482	$6,694	$13,632	$21,347	$28,517	$35,639	66.47%
364	Muncie, IN	$3,424	$7,980	$15,709	$23,822	$27,657	$35,762	66.70%
363	Ocala, FL	$2,902	$6,672	$15,155	$22,221	$29,079	$35,864	66.89%
362	Beckley, WV	$2,464	$6,913	$12,552	$19,975	$29,477	$35,948	67.05%
361	Fort Smith, AR-OK	$2,678	$6,826	$13,653	$20,686	$28,685	$35,968	67.08%
360	Gadsden, AL	$2,969	$7,311	$14,079	$20,862	$29,162	$36,069	67.27%
359	Gulfport-Biloxi-Pascagoula, MS	$3,413	$7,280	$13,874	$23,283	$33,558	$36,175	67.47%

Regression Results

To explain the basis for such large changes in MSA rank order over time, a regression model was developed that includes both quantitative variables related to the structure and demographic variability between the MSAs and fixed effects variables that control for regional differences. The following model was specified to explain the differences in the change in rank order over the 44 year period from 1969 to 2017:

$$CHANG\ E_i = B_0 + B_1POPPC_i + B_2SP12_i + B_3DENS_i + B_4PUB_i + B_5PRI_i + B_6DME_i + B_7DGL_i + B_8DPL_i + B_9DSE_i + B_{10}DSW_i + B_{11}DRM_i + B_{12}DFW_i + E_i$$

Where:

$CHANGE_i$ =	Change in the MSA PCPI rank order between 1969 and 2017.
$POPPC_i$=	Percentage change in MSA population between 1969 and 2017.
$SP12_i$ =	Service sector employment as a percent of total employment 2012.
$DENS_i$ =	MSA population density in 2010.
PUB_i =	The existence of a top 200 public research university within the MSA.
PRI_i =	The existence of a top 200 private research university within the MSA.
DME_i=	A regional dummy with a value of 1 if the state is in the Mideast BEA Region and 0 otherwise.
DGL_i=	A regional dummy with a value of 1 if the state is in the Great Lakes BEA Region and 0 otherwise.
DPL_i=	A regional dummy with a value of 1 if the state is in the Plains BEA Region and 0 otherwise.
DSE_i=	A regional dummy with a value of 1 if the state is in the Southeast BEA Region and 0 otherwise.
DSW_i=	A regional dummy with a value of 1 if the state is in the Southwest BEA Region and 0 otherwise.
DRM_i=	A regional dummy with a value of 1 if the state is in the Rocky Mountain BEA Region and 0 otherwise.
DFW_i=	A regional dummy with a value of 1 if the state is in the Far-West BEA Region and 0 otherwise.

The data for all the quantitative variables was from the BEA Regional Economic Accounts. The omitted region for the qualitative variables was for the New England region. Thus, the coefficients on the included regional variables are to be interpreted as the predicted difference in the percentage rank order over the 49 year period for a given MSA in a given region, versus an MSA located in the New England region.

The model was estimated for the 383 MSAs using an OLS regression model and White heteroske dasticity-consistent standard errors and covariance. The regression results are reported in Table 7. This model has an R-squared value of 0.2332 and an F-statistic that tests significant at the 0.01 level.

Table 7. Regression Results

LS // Dependent Variable is CHG2017

Included observations: 383

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	79.0580	17.6031	4.4912	0.0000
POPPCi	-4.5246	4.2266	-1.0705	0.2851
SP12i	-1.8470	0.3712	-4.9760	0.0000
DENSi	-0.0204	0.0105	-1.9408	0.0530
PUBi	29.0722	10.5042	2.7677	0.0059
PRIi	10.8576	12.5686	0.8639	0.3882
DME_i	-25.2252	15.3773	-1.6404	0.1018
DGL_i	-72.1844	16.3507	-4.4148	0.0000
DPL_i	-14.8264	18.8459	-0.7867	0.4320
DSE_i	-11.5322	14.9180	-0.7730	0.4400
DSW_i	-61.9896	19.9852	-3.1018	0.0021
DRM_i	-34.5611	19.0347	-1.8157	0.0702
DFW_i	-93.1890	17.1842	-5.4230	0.0000
R-squared	0.233181	Mean dependent var		0
Adjusted R-squared	0.208312	S.D. dependent var		92.54222
S.E. of regression	82.34118	Akaike info criterion		8.855096
Sum squared resid	2508626	Schwarz criterion		8.989102
Log likelihood	-2226.204	F-statistic		9.376085
Durbin-Watson stat	2.062352	Prob (F-statistic)		0

Population percent change: The coefficient on the percent change in population between 1969 and 2017 is not significant at the 0.05 level.

Service sector employment: The coefficient for the percent of the MSA's employment within the service sector in 2010 has a negative sign and is significant at 0.01 level. The coefficient for the percent of the MSA's service sector employment is -1.8470.The coefficient indicates that there may be a negative relationship between the relative size of the service sector and a change in the MSA's rank over the 49 year period.

Density: The coefficient for the population density of the MSA in 2010 has a negative sign and tests significant at 0.10 level. The coefficient for population density is -0.0204, suggesting that increased MSA density has a small negative impact on the MSA rank change over the 49 year period.

Public research university: The coefficient for the presences of a public research university ranked in the top 200 by US News and Report in 2012 has a positive sign and tests significant at 0.05 level. The coefficient for the presence of a public university is 29.0722. The coefficient indicates that for the presence of a top 200 public university there is an expected 29.0722 unit increase in the MSA's rank over the 49 year period.

Private research university: The coefficient for the presences of a private research university ranked in the top 200 by US News and Report in 2012 has a positive sign but does not test significant at 0.10 level.

Regional effects: Three of the coefficients on the regional dummy variables (DGL, DSW, and DFW) have negative signs and test significant at the 0.05 level. MSAs in the Great Lakes region, the Southwest region, and the Far West region all have negative coefficients that indicate that, on average, MSAs within those regions suffered a double digit decline in their rank order compared to MSAs in the control dummy, the New England region. In addition, the regional dummy coefficient for the Mideast region (DME) also has a negative sign but statistically insignificant sign. MSAs within this region suffered a 25.2252 decline in their rank order compared to MSAs in the control dummy, the New England region

5. Conclusion

The growth of PCPI for MSAs, 1969 to 2017, exhibits a high level of variability in a number of dimensions. The ratio of the maximum PCPI to the minimum has an upward trend, growing from 3.4190 to 4.2980. The ratio fluctuates substantially between the beginning and end period. Comparing quintile rankings based on 1969 PCPI with rankings based on 2017 PCPI indicates that New England, Plains, Southeast, and Southwest regions moved up the rankings while MSAs in the Great Lakes and Far West regions moved down. The Mideast and Rocky Mountain regions showed mixed results.

Changes in rank are indicative of mobility across the dynamic income distribution. With 383 MSAs and a relatively narrow band of PCPI, frequent changes in rank are expected. The changes in rank are notably large, ranging from -164 positions to +207 positions in a single year.29 MSAs (7.6%) experience a decline in rank of over 150 positions. While 20 MSAs (5.2%) experience an increase in rank of over 150 positions.

The regression results suggest that changes in MSA PCPI rank over the 49 year period are negatively affected by the size of the service sector, and the MSA's population density. In addition, the regional location of the MSA can also have a negative impact on the change in rank over the 49 year period. MSAs in the Great Lakes region, the Southwest region, and the Far West all experience a negative and significant decline in their PCPI ranking. The only variable that generated a positive and significant impact of the PCPI ranking over time was the presence of a top 200 public research institution within the MSA.

Our results have important implications for the widely publicized urban-rural divide as well as for recent claims regarding the economic importance of a handful of superstar cities. A 2019 *Federal*

Reserve Bank of St Louis study by Charles Gascon and Brian Reinbold portrays the rather stark economic differences between rural and urban areas. For example, Gascon and Reinbold find median growth rates of 1.7% for metro counties as compared to 1.18% for non-metro counties. Our findings regarding divergent PCPI growth across MSAs demonstrates that differences run deeper than urban vs rural distinctions. The widening gap between high and low performing metropolitan areas over time provides particularly strong evidence of performance differences across urban America.

It is also true that differences in economic performance across metro areas are more complex than recent reporting for subgroups of cities suggests. Considerable attention has been directed to the role of so called superstar cities as engines of dynamic innovation and economic growth. A December 2018 *Wall Street Journal* article by Christopher Mims chronicles the economic impact and concentration of wealth found in a dozen leading US cities. Key criteria for inclusion on the list of superstar cities are availability of technical employment opportunities and degree of digitalization in the workplace. While the dozen superstar cities do figure prominently in our list of top 25 US MSA's by PCPI, superstar cities do not dominate upward urban mobility as only two MSAs, Durham-Chapel Hill, NC and Austin-Round Rock TX, appear on our grouping of cities with the largest positive changes in PCPI ranking. Our results point to the successes of cities outside the superstar grouping and are consistent with the work of Jackson *et al.* (2018) of the Milken Institute which suggests available opportunities for metropolitan areas to choose different paths to success. According to Jackson *et al.,* the appropriate path for each city depends upon their industry mix, policy discretion and resource availability. In addition to technology and digitalization, Jackson *et al.,* point to the importance of defense industries, health and medical facilities, college towns, as well as logistics and/or manufacturing hubs as drivers of success among less prominent metropolitan areas.

The results of this paper provide a caution to all who believe that the disparity in PCPI is either a rural/urban divide, a superstar/all other MSA divide, or a regional divide. The degree to which some MSAs PCPI rank changed over the 49 year period is staggering. Twenty-five MSAs had negative PCPI rank changes of between 165 and 245 positions (out of 383 total MSAs). Twenty-five MSAs had positive PCPI rank changes between 135 and 338 positions. Only two superstar MSAs show up in the list of the 25 MSAs with the largest positive PCPI rank change over the 49-year period. Finally, for the 25 MSAs that had the greatest positive change in PCPI, 7 of the BEA regions were represented (none in the Far West) and for the 25 MSAs that had the greatest negative change in PCPI, 6 of the BEA regions were represented (none in New England and Rocky Mountains).

While this paper provides an understanding of how significant changes in MSA PCPI has occurred over the past 49 years it also opens up questions of how MSAs can improve their level of PCPI and impact their individual PCPI ranking amongst other MSAs. Ideas for further research can address specific public policy changes that can influence both positive and negative movement in MSA PCPI levels and rankings.

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