THE IMPACT OF CREATIVE CLASS EMPLOYMENT ON METROPOLITAN POPULATION GROWTH

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THE IMPACT OF CREATIVE CLASS EMPLOYMENT ON METROPOLITAN POPULATION GROWTH

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The role of workers in occupations that require high levels of creative thinking and problem solving on metropolitan area growth in the U.S. is explored. Richard Florida (2002) labeled workers in these occupations as the creative class, and hypothesizes that they play a crucial role in growth of metropolitan areas over time. A formal statistical examination of the impact of employment in creative class occupations on population growth in a cross-section of 367 US metropolitan areas over the period 2005 to 2010 is undertaken in this thesis.

CHAPTER 1

INTRODUCTION

1.1 Brief background

The creative class is a class of workers first penned by Richard Florida (2002) in his book, The Rise of the Creative Class, to describe those occupations that require high levels of creativity and whose workers add value to their occupations by thinking creatively and applying their talents to solve problems and drive innovation in unique ways. Florida characterized the creative class by their occupational classifications such as engineers, architects, postsecondary teachers, and financial analysts to name a few. However, a reclassification of creative occupations was done by the Economic Research Service in 2007, which eliminated certain occupations where employees were not believed to be required to think creatively. The resulting creative class was comprised of 231 unique occupational classifications. Despite the reclassification of the creative class, Florida's primary thesis remains consistent.

Florida (2002) contends that the creative class drives growth in urban centers around the United States and metropolitan areas that attract these employees grow at a faster rate than those urban centers that do not. He contends that the interaction between creatively oriented, high human capital individuals in densely populated areas creates knowledge spillovers. This transmission of new ideas is promoted in socially diverse metropolitan areas where it is asserted that certain regions reinforce the frequent interaction of creative individuals and facilitate the production of new knowledge.

We evaluate Florida's hypothesis using a conventional population growth regression which tests for convergence in levels of population in a cross section of cities across the United States. Convergence occurs if smaller cities grow faster than larger cities, since this implies a catching-up of smaller with larger sized cities and thus we would see the population spreading out more evenly across regions. In contrast, if larger cities grow faster (or at an equal rate) as their smaller counterparts, we will see divergence, where the gap in population levels between cities grows over time and people tend to concentrate in a smaller group of cities. In this thesis we are concerned with the overall positive net migration of people into metropolitan areas and because population growth includes birth rates, death rates, in-migration, and out-migration, we focus our attention on net migration and use population growth as a proxy. This is a reasonable assumption because the magnitude and variation of the net difference between the rate of births and deaths over the regions of interest is much smaller than that of the net migration in these same regions and thus would not make a significant impact on our results.

The statistical importance of creative class employment is considered in the context of the population growth regression. We test whether the proportion of creative class employment in a city exerts a positive and significant impact on population growth over the period 2005 to 2010, after controlling for the initial period level of population. Calculating the proportion of creative class employment in our sample of 367 US metropolitan areas involves use of a 2007 classification of creative occupations by the U.S. Department of Agriculture Economic Research Service (McGranahan and Wojan, 2007). This is comprised of 231 occupational classifications from the US Bureau of Labor Statistics annual Occupational Employment Survey. This refinement of Florida's original list of creative class occupations was undertaken to better capture the occupations that truly embodied innovative activity and creative capital.

Much of the emphasis in the literature on creative class impacts on cities is concerned with the attraction of in-migrants (see for example: Wojan, Lambert and McGranahan, 2007). Population growth is used here as a proxy for metropolitan growth arising from net migration. By definition, annual population growth is annual births minus deaths and in-migration minus out-migration. To the extent that births and deaths are similar across the sample of metropolitan areas, population growth reflects variation mostly due to net migration (in- minus out-migration). We use a similar population growth proxy in our analysis.

In addition to estimating growth regressions based on the overall proportion of the creative occupational employment in our metropolitan areas, we also estimate growth regressions augmented with sub-categories of creative class occupations, for example: computer and mathematics workers, architecture, science and faculty in higher education. We break out the eight creative class occupations and estimate a regression coefficient for each one that potentially influences population growth in each metropolitan area. These relationships test for the relative importance of different types of creative class employment on population growth. The results provide us with a finer understanding of each creative occupation and how the proportion of their respective employment levels influence net migration across our cross section of cities. One would naturally postulate that each occupational category should facilitate different rates of net migration and surely would not all be the same.

The impact of creative class employment on population growth is also considered using population growth (over the 2005 to 2010 period) for varying age groups, using 5 year age increments for metropolitan area population between the ages of 20 and 69. This is motivated from the understanding that people of different age groups, while all embodying creative capital, migrate to different places based on individual preferences regarding such things as family and health needs based on their age. The results will show that certain age groups of creative employees migrate towards or away from regions with varying proportions of creative occupations. For example, one might propose that creative individuals in the age group 20-24 would migrate less towards regions with high densities of management (a creative occupational category) while they might migrate more towards regions with a high density of sales occupations due to their experience level, high energy, and the lower entry barriers into this type of occupation.

An alternative to the regression based tests for the impact of creative class employment on population growth is also carried out. This involves comparing our 367 metropolitan area distributions of occupational employment in the 231 occupational classifications that make up the creative class. This was used to find a "twin" for each of the 367 metropolitan areas, where by twin we mean the metropolitan area with the most similar distribution of creative class employment among the 231 occupations. Using the population growth rates partitioned by the 5 year age increments from the ages 20 to 69, we determine the correlation between growth rates of the 367 metropolitan areas and their twins over the years 2005 to 2010. If the occupational composition of creative class employment is an important determinant for metropolitan area population growth, we would expect to see high correlations between metropolitan areas with similar distributions of creative class occupations. For each age group we identify the two most similar metropolitan areas in terms of creative class occupational proportions ("twin 1" and "twin 2") and calculate the overall correlation between population growth of these twins for all 367 metro areas. If creative class employment is a significant determinant of net migration then we should expect to see high population growth rate correlations between the cities and their twins due to the similarity of their creative occupation distributions.

1.2 Significance of research

There is a great deal of interest in factors that influence the population growth of cities. Understanding the role played by different types of workers in the process of metropolitan area growth has a great many policy implications. Urban and regional policy is aimed at attracting the highest quality residents that will produce innovation and interaction; the aim of this is to support knowledge spillover, technology leveraging, and industrial R&D investment. These results have been seen to support affluence and diversity within communities. Combes, Duraton, and Gobillon (2007) find evidence that workers select places to live that maximize their earnings, so metropolitan areas with a large proportion of creative class workers could attract even more workers of this type, leading to a divergence situation. This would mean that high growth cities grow even more rapidly and consist of workers with higher earnings. Therefore if these results are valid then regions seeking innovative economic growth should invest in an infrastructure that mediates high creative class densities and thus greater urban innovative capacity.

Echeverri-Carroll and Ayala (2009) find that similar workers in metropolitan areas with higher-skilled workers earn higher wages, when controlling for a host of other determinants of earnings. This would provide another motivation for the attractive force of creative class workers in a metropolitan area. Echeverri-Carroll and Ayala (2011) provide empirical evidence that city size is not as important as the presence of knowledge workers in determining metropolitan area earnings. Again, urban areas would benefit by reinforcing the determinants of innovation such as human capital, environments of knowledge exchange, and density-induced interactions that would all support positive net migration of the creative class.

Finally, Glaeser and Gottlieb (2008) explore general issues associated with national and local urban policies as they impact the types of cities that arise and success versus failure in terms of economic growth. These policies could also play a role in the distribution of creative class workers across metropolitan areas.

Urban and regional policy plays critical roles in the development of cities across the United States. Understanding the determinants of the various characteristics such as innovation, growth, and the interaction of people within a city can better assist in the realization of a developed urban core. This thesis will provide key insights into the determinants of migration into metropolitan areas that are determined through various proportions of creative class occupational categories.

1.3 Limitations

We would like to address the limitations in this thesis where our methods of analysis could be weak or differ from those of previous studies. First, we do not include data that relate to the creative class such as the number of patents issued in certain metropolitan areas. Often the number of patents issued by companies and individuals in a region directly relates to the concentration of creative capital and innovation spillover in a region. We feel that our creative class occupational employment proportions do well to proxy this variable but there still remains the opportunity to further refine the study by directly adding this variable into our population growth models.

We do not attempt to model innovation as much of the past research has focused on. There has been a significant amount of research carried out in an effort to model the innovative capital in regions across the United States. This research models the determinants of innovation and helps facilitate urban and regional policy directed at promoting this within urban areas. This is not within the scope of this thesis and therefore has been intentionally left out.

Our growth model limits the number of explanatory variables to only occupational classifications without controlling for other variables such as number of patents or amount of investment in R&D. We do control for initial population but do not focus on multiple independent variables to explain the variation in population growth.

Finally, we are not controlling for the variation in the location of the cities that could influence migration and thus population changes. Spatial dependence in population growth should be investigated in a separate study and could easily be an entire topic unto itself. There is likely a relation between population growth and migration locations, however it is beyond the scope of this thesis.

A limitation of our data is that employment data for occupational categories across the United States do not include self-employed individuals or businesses with less than 20 employees. This could pose a significant change to our results because we believe that some of the most creative individuals are those who start their own businesses. These are individuals with a lot of creative capital in both technical and business expertise. However, the results would certainly vary according to the total proportion of creative class represented by these individuals and this should be the topic of future research and data collection efforts.

CHAPTER 2

GROWTH REGRESSIONS

2.1 Metropolitan population growth

There is a great deal of interest in population and income growth for countries, regions and metropolitan areas as indicated by the large amount of literature on economic growth from both a theoretical and empirical perspective. Barro and Sala-i-Martin (1998) provide a theoretical analysis while Barro and Sala-i-Martin (1991) provide an empirical study.

The basic methodology that has been developed involves a growth regression, which calculates the intercept and slope for a relationship between (in our case) population growth for each metropolitan area over the period 2005 to 2010 and the initial period 2005 (logged) population levels.

> Vector of Growth rates = $log(y_T) - log(y_0)$, where y_T is the vector of 367 values taken by the $n \times 1$ variable vector y (population in our case) at the end period denoted by T. The vector y_0 represents the values taken by the variable at the beginning period 0.

In our case, $T = 2010$ and $0 = 2005$, so we have:

$$\begin{aligned} (\log(y_T) - \log(y_0))/5 &= \alpha\iota_n + \beta\log(y_0) + \varepsilon \qquad (2.1) \\ \varepsilon &= N(0, \sigma^2 I_n) \end{aligned}$$

To convert the growth rates (measured by $\log(y_T) - \log(y_0)$) to annualized growth rates, we divide by the number of years (5 in our case, for 2005 to 2010).

If the slope coefficient is negative and statistically significant, this is interpreted to mean that smaller metropolitan areas exhibit higher growth rates, which will over time result in convergence in population levels across the metropolitan areas. This is because smaller metropolitan areas are growing faster than larger population areas, resulting in a catching-up phenomena. In contrast, if we find a positive and statistically significant coefficient, the implication is divergence, since larger areas are growing faster than smaller metropolitan areas, leading to an increase in the size gap.

2.2 Data used for growth regressions

The information needed to produce growth regressions included: estimates of population by metropolitan area, occupational employment levels for creative class workers, and a mapping of counties to metropolitan areas. Each of these is described in the following sections.

2.2.1 Occupational employment statistics

The Bureau of Labor Statistics, Department of Labor reports a series of survey results from their Occupational Employment Statistics (OES) Survey, each May on their website: http:/stat.bls.gov/oes/home.htm, which records employment as well as average and median annual earnings information in 817 different occupational classifications. These are reported by state and metropolitan area, with our focus on metropolitan area information.

Occupational classifications take the form of 22 major job categories, plus a total ‘all occupations’ category, and 794 different subcategories. Information is not available for all occupational classifications for all metropolitan areas. For example the Los Angeles-Long Beach-Glendale, CA Metropolitan Division, one of the larger metropolitan areas, contains only 734 different occupational classifications in the year 2008.

The 22 major job categories are shown in Table 2.1. As an illustration of the subcategories within the major category of *Computer and mathematical*, table 2.2 shows these 16 different categories. One point to note is that the Occupational Survey information does not include self-employed workers, since it is an employer-based survey.

Table 2.1: Major occupational classification categories

Code	Occupation
000000	All Occupations
110000	Management occupations
130000	Business and financial operations occupations
150000	Computer and mathematical
170000	Architecture and engineering
190000	Life, physical, and social science
210000	Community and social services
230000	Legal
250000	Education, training, and library
270000	Arts, design, entertainment, sports, and media
290000	Healthcare practitioners and technical
310000	Healthcare support
330000	Protective service
350000	Food preparation and serving related
370000	Building and grounds cleaning and maintenance
390000	Personal care and service
410000	Sales and related
430000	Office and administrative support
450000	Farming, fishing, and forestry
470000	Construction and extraction
490000	Installation, maintenance, and repair
510000	Production
530000	Transportation and material moving

For this thesis, a subset of the 817 occupational employment categories was used to form creative class employment in each of the 367 metropolitan areas. This involved use of a set of 231 occupational classifications provided by the USDA Economic Research Service, documented in McGranahan, and Wojan (2007).

Table 2.2: Minor occupational classification categories

Occupation	subcategory code
Computer and information scientists, research	151011
Computer programmers	151021
Computer software engineers, applications	151031
Computer software engineers, systems software	151032
Computer support specialists	151041
Computer systems analysts	151051
Database administrators	151061
Network and computer systems administrators	151071
Network systems and data communications analysts	151081
Computer specialists, all other	151099
Actuaries	152011
Mathematicians	152021
Operations research analysts	152031
Statisticians	152041
Mathematical technicians	152091
Mathematical scientists, all other	152099

2.2.2 Metropolitan areas

Metropolitan areas consist of one or more contiguous counties, where the area is defined based on a central urban county and contiguous (borders touching) neighboring counties that meet specified requirements regarding population commuting to or from the central counties.

Standard definitions of metropolitan areas were first issued in 1949 by the then Bureau of the Budget, a predecessor of the Office of Management and Budget (OMB), who now provides the formal definitions of metropolitan areas. Over time the formal term used to define metropolitan areas has changed from "standard metropolitan area" (SMA) to "standard metropolitan statistical area" (SMSA) in 1959, and to "metropolitan statistical area" (MSA) in 1983. The term "metropolitan area" (MA) was adopted in 1990 and referred collectively to metropolitan statistical areas (MSAs), consolidated metropolitan statistical areas (CMSAs), and primary metropolitan statistical areas (PMSAs). The term "core based statistical area" (CBSA) became effective in 2000 to denote both metropolitan and micropolitan statistical areas.

The 2000 standards provide that each CBSA must contain at least one urban area of 10,000 or more population. Each metropolitan statistical area must have at least one urbanized area of 50,000 or more inhabitants. Each micropolitan statistical area must have at least one urban cluster of at least 10,000 but less than 50,000 population.

Under the standards, the county (or counties) in which at least 50 percent of the population resides within urban areas of 10,000 or more population, or that contain at least 5,000 people residing within a single urban area of 10,000 or more population, is identified as a “central county” (counties). Additional “outlying counties” are included in the CBSA if they meet specified requirements of commuting to or from the central counties. Counties or equivalent entities form the geographic “building blocks” for metropolitan and micropolitan statistical areas throughout the United States.

As of June 6, 2003, there are 362 metropolitan statistical areas and 560 micropolitan statistical areas in the United States. These were re-defined based on the year 2010 Census information, which resulted in 367 metropolitan areas.

Using the counties which form the basis of metropolitan/micropolitan areas, we converted the county level annual population information to produce metropolitan area population. We then converted this to our respective population growth rates.

2.2.3 County population estimates

The US Census Bureau produces annual population estimates by county for age groups in five year increments. Data for county population by age groups over the period April 1, 2005 to July 1, 2010 were used to form metropolitan area population numbers by aggregating county-level figures to metropolitan areas.

The map in Figure 2.1 shows a county map for the lower 48 states (and the District of Columbia) with metropolitan area counties presented using the color black.

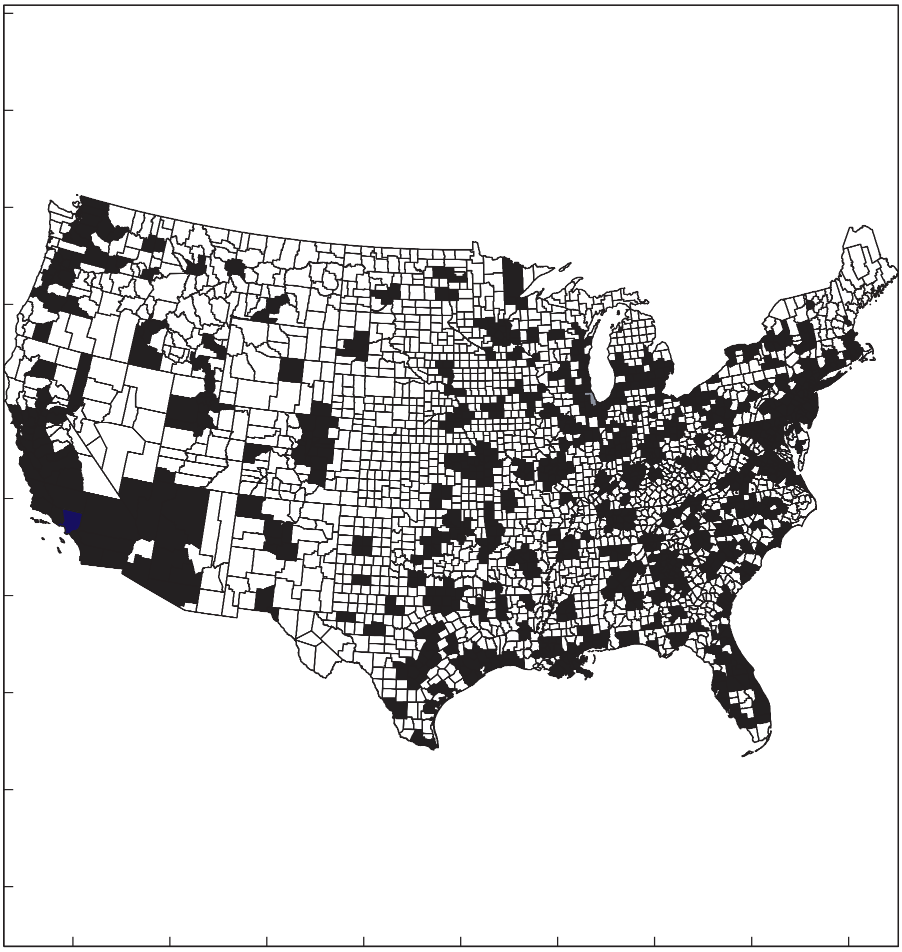

Figure 2.1: Metropolitan area counties used

2.3 Empirical results for a metropolitan area growth regression

The results from a growth regression of population growth over the 2005 to 2010 period on the logged initial period population level are shown in Table 2.4, along with results from an augmented regression that includes the proportion of creative class employment as an explanatory variable. These were carried out using publicly available MATLAB programs documented in LeSage (1999).

Table 2.3: Growth regression results for population 2005-2010

Variables	Coefficient	t-statistic	$t-$probability
constant	0.0273	1.0272	0.3049
log(pop2005)	0.0016	0.7873	0.4315
R-squared	0.0017		
Nobs	367		
Variables	Coefficient	t-statistic	$t-$probability
constant	0.0701	2.0684	0.0393
log(pop2005)	-0.0031	-0.9943	0.3207
proportion creative employment	0.1469	2.0208	0.0440
R-squared	0.0128		
Nobs	367		

From the results we see no evidence of convergence or divergence in population across the metropolitan areas since the slope coefficient (log(pop(2005)) is not statistically significantly different from zero as indicated by the t-statistic.

A lack of convergence or divergence is also evident in the augmented regression that includes the proportion of creative class employment as an additional explanatory variable. The variable reflecting creative class employment has a positive and statistically significant coefficient estimate at the 95% significance level. This finding is consistent with Florida's argument that creative class employment promotes growth of cities.

2.4 Results by age groups

The same regressions were carried out for population growth by age groups beginning with age 20-24 up to age 64-69 in five-year increments. This allows an examination of the role played by creative class employment in attracting various age groups to metropolitan areas. Results are shown in Table 2.4, where we have omitted intercept term estimates to conserve on space.

We have divergence for ages 20-24, 40-44, 45-49, 50-54, which suggests population in these age groups was concentrating in certain metro areas. Ages 20-24 locating in large metro areas has been noted in the popular press. Ages 40-54 is a prime working age group with older children.

We have convergence for ages 25-29, 30-34, 54-59, 60-64, and 65-69 which suggests population for these ages was spreading out evenly among the metro areas. Ages 54-69 are the baby boomers and ages 25-34 are people likely to be starting families.

We have neither convergence nor divergence for ages 35-39, which points to no particular pattern of location.

2.5 Results by occupational groups

Rather than aggregate all creative class occupations to produce a single proportion of total employment in creative class jobs, we can consider the significance of sub-categories of creative class workers. We interpret positive and significant coefficients for a particular occupational class as an indication that this type of employment attracts immigrants to a metropolitan area. Similarly, we interpret a negative and significant estimate as an indication that this type of employment acts as a push factor to generate out- migration. Of course, these coefficients reflect partial derivatives for how changes in the proportion of employment in each category impacts metropolitan area population growth. Recall, we are treating metropolitan population growth or decline as if it arises from in- and out-migration, abstracting from variation in birth and death rates across the cities.

The results for the age group 20-24, including occupational class subcategories, continues to show divergence. Young people are moving to metro areas with a higher proportion of sales jobs and moving away from metro areas with arts and business employment concentrations.

We have convergence for ages 25-29. These ages are moving to metro areas with science and arts and avoiding metro areas with management employment.

We see overall convergence for the age group 30-34, indicating that this age group is moving into smaller cities faster than larger ones. This population is moving towards cities with science occupations and away from cities with a higher proportion of educational occupations. One note to make is that our educational category represents higher education, not primary and secondary. This is a deviation from Florida's creative class occupational classification which includes primary and secondary teachers. Thus areas with a large proportion of educational occupational employment would include cities with colleges and universities. This essentially means that this age group is avoiding college towns.

The age group 35-39 shows neither convergence or divergence, however persons in this age group move away from areas with high densities of business and education employment. They do in fact move toward areas with higher proportions of management occupations. This makes intuitive sense as this is a prime age group for beginning management careers.

The age group 40-44 shows divergence and people in this age group move away from areas with business, architecture, and education occupational employment. They move towards cities with a lot of management employment.

The age group 45-49 shows divergence as well and population in this age group move away from areas with occupations of architecture, arts, education, and science, while they move to areas with employment in computer-related industries.

The age group 50-54 also shows divergence; this age group moves away from areas characterized by the arts and science. They move towards areas with computer-related occupations.

The age group 55-59 shows convergence and is characterized by people moving towards areas with localized concentrations of the arts.

The age group 60-64 shows convergence and people in this age group move to areas with high concentrations of management, arts, and science occupations.

The age group 65-69 shows convergence; people in this age group move towards areas with management and science occupations while they move away from areas with business and education clustering.

We see an overall population migration away from areas that are densely occupied with business, architecture, and education employees. We see greater in-migration to areas with occupations of management, sales, science, and computer. Cities with concentrations of the arts show a split between in- and out-migration across the age groups. The ages 25-34 and 55-69 show convergence while the age groups 20-24 and 44-54 show divergence.

Convergence indicates that persons in these age groups are spreading more evenly across our sample of metropolitan areas. Divergence for an age group points to concentrations of people in a smaller set of cities. Using this reasoning, baby boomers in the 54-69 ages appear to be spreading out evenly across the cities, with more equal number of these expected in all cities. In contrast, the 20-24 and 44-54 age groups are diverging, which implies increasing concentrations of these people in a smaller group of cities.

2.6 Metropolitan area twins

To further evaluate the effect that the creative class has on population growth, we compare metropolitan areas that share similar creative class occupational distributions. Specifically, the vector of 231 occupational proportions for the creative class in each city was correlated with that from all other cities. The city with the highest correlation was labelled “twin 1” since this city exhibits the most similar distribution of creative class employment. The city with the second highest correlation was labelled “twin 2” since this is the city with the second most similar distribution of creative class employment across the occupational categories. We find the two metropolitan areas that have the greatest similarity of creative class distribution and name these “twin 1” and “twin 2” respectively for each of the 367 MSAs.

Based on our premise that creative class occupational employment drives net positive migration and thus positive population growth, we should see similar population growth rates among the MSAs and their twins. For each age group we found the growth rate correlation among the vector of MSAs and their respective twins. These results are shown in table 2.15.

We see that the highest correlation is 0.3775, which indicates a weak relationship between creative class distribution and growth rates among MSAs. This result is somewhat inconsistent with Richard Florida’s argument that it is the creative class that drives urban population growth. While creative occupational employment certainly is a factor that promotes net in-migration in metropolitan areas, our research does not indicate that it is as a significant a source of determination as Florida would argue.

2.7 Closing

Richard Florida's underlying contention is that companies and cities alike are now working to attract the creative class more than ever before and the creative class drives positive net migration and population growth in metropolitan areas. He believes that creative human capital is the greatest strategic asset that economies can leverage for innovation and growth in the 21st century. Florida stresses that cities should do everything in their power to foster creative class in-migration to their urban cores thus promoting an innovative economy of knowledge spillover and urban creative capacity.

While it is certainly true that creative capital can and should be leveraged by companies and cities alike, we have found in our research that the creative class is not as significant a determinant of population growth as Florida contends. Creative people that are in an interactive environment will share ideas, exchange knowledge, and promote innovation. They are not however the drivers of urban population growth. People move to places based on all types of determinants including family proximity, weather, career opportunity, social diversity, and taxes to name a few. They are to a lesser extent concerned directly with the density and quantity of their fellow creative class peers.

All in all, urban policy and planning should focus on promoting innovation and affluence within the urban core. Diversity and creativity are important factors that reinforce a city's identity and should be considered in the development of an area's infrastructure. Focusing only on attracting the creative class in hopes of promoting population growth though may not provide the total solution for urban centers; it is a fine supplement to an overall developmental policy though. Cities and communities alike should support and leverage their creative human capital; a greater density of highly-skilled and capable individuals will produce innovation and drive economies into the 21st century.

Table 2.4: Growth regression results for population by age 2005-2010

	Ages 20-24		
Variables	Coefficient	t-statistic	$t-$probability
log(pop0)	0.0133	2.8473	0.0047
creative proportion	0.1075	1.0191	0.3088
R-squared	0.0772		
	Ages 25-29		
log(pop0)	-0.0345	-5.4829	0.0000
creative proportion	0.6416	4.2174	0.0000
R-squared	0.0763		
	Ages 30-34		
log(pop0)	-0.0121	-2.3722	0.0182
creative proportion	0.2227	1.8058	0.0718
R-squared	0.0152		
	Ages 35-39		
log(pop0)	-0.0074	-1.2734	0.2037
creative proportion	0.0798	0.5618	0.5746
R-squared	0.0055		
	Ages 40-44		
log(pop0)	0.0113	2.4083	0.0165
creative proportion	-0.0698	-0.6185	0.5366
R-squared	0.0248		
	Ages 45-49		
log(pop0)	0.0084	1.9300	0.0544
creative proportion	0.0496	0.4800	0.6315
R-squared	0.0336		
	Ages 50-54		
log(pop0)	0.0091	2.3545	0.0191
creative proportion	0.0155	0.1723	0.8633
R-squared	0.0386		
	Ages 54-59		
log(pop0)	-0.0211	-5.4980	0.0000
creative proportion	0.4680	5.2799	0.0000
R-squared	0.0838		
	Ages 60-64		
log(pop0)	-0.0216	-5.2913	0.0000
creative proportion	0.7116	7.6357	0.0000
R-squared	0.1384		
	Ages 65-69		
log(pop0)	-0.0139	-2.9764	0.0031
creative proportion	0.6232	5.9318	0.0000
R-squared	0.0953		

Table 2.5: Growth regression for population for ages 20-24 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	-0.1539	-3.6687	0.0003
log(pop0)	0.0130	2.5725	0.0105
management	0.5091	1.1664	0.2442
business	-0.8267	-1.7532	0.0804
architecture	0.6712	1.2084	0.2277
sales	1.4203	3.0290	0.0026
arts	-2.5140	-1.9861	0.0478
education	0.5697	0.6141	0.5395
science	-0.2814	-0.1889	0.8503
computer	0.5858	0.9474	0.3441
R-squared	0.1195		

Table 2.6: Growth regression for population for ages 25-29 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	0.4071	7.7151	0.0000
log(pop0)	-0.0331	-4.8224	0.0000
management	-1.2832	-2.0533	0.0408
business	0.0071	0.0107	0.9915
architecture	-0.4172	-0.5320	0.5951
sales	0.0717	0.1058	0.9158
arts	4.1781	2.3690	0.0184
education	-0.5156	-0.3987	0.6903
science	4.4416	2.1176	0.0349
computer	1.2662	1.4550	0.1465
R-squared	0.1311		

Table 2.7: Growth regression for population for ages 30-34 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	0.0968	2.2479	0.0252
log(pop0)	-0.0107	-1.9036	0.0578
management	0.7341	1.4454	0.1492
business	-0.2933	-0.5398	0.5897
architecture	0.2085	0.3268	0.7440
sales	0.2758	0.4974	0.6192
arts	1.8560	1.2950	0.1961
education	-2.8520	-2.7096	0.0071
science	4.6714	2.7351	0.0065
computer	-0.5217	-0.7368	0.4617
R-squared	0.0547		

Table 2.8: Growth regression for population for ages 35-39 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	0.0071	0.1463	0.8838
log(pop0)	-0.0057	-0.8940	0.3719
management	1.8702	3.2264	0.0014
business	-1.3605	-2.1802	0.0299
architecture	-0.4673	-0.6377	0.5241
sales	0.1962	0.3068	0.7592
arts	1.3089	0.8014	0.4234
education	-3.3015	-2.7318	0.0066
science	1.9577	0.9998	0.3181
computer	0.6690	0.8242	0.4104
R-squared	0.0689		

Table 2.9: Growth regression for population for ages 40-44 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	-0.2535	-6.4887	0.0000
log(pop0)	0.0192	3.8065	0.0002
management	1.2045	2.7052	0.0072
business	-1.8781	-3.8964	0.0001
architecture	-1.6236	-2.8669	0.0044
sales	-0.4240	-0.8547	0.3933
arts	-1.6033	-1.2742	0.2034
education	-2.8287	-3.0333	0.0026
science	2.4105	1.5979	0.1109
computer	2.1124	3.3752	0.0008
R-squared	0.1354		

Table 2.10: Growth regression for population for ages 45-49 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	-0.1388	-3.7258	0.0002
log(pop0)	0.0151	3.1535	0.0017
management	0.5198	1.2635	0.2072
business	-0.4817	-1.0801	0.2808
architecture	-0.9643	-1.8363	0.0671
sales	0.0955	0.2074	0.8358
arts	-3.0983	-2.6548	0.0083
education	-1.9323	-2.2360	0.0260
science	-3.0613	-2.1962	0.0287
computer	2.5595	4.4140	0.0000
R-squared	0.1240		

Table 2.11: Growth regression for population for ages 50-54 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	-0.0362	-1.1123	0.2667
log(pop0)	0.0147	3.4724	0.0006
management	0.0179	0.0506	0.9597
business	0.0050	0.0131	0.9896
architecture	-0.1870	-0.4144	0.6789
sales	0.0254	0.0640	0.9490
arts	-3.1366	-3.1177	0.0020
education	-0.8687	-1.1698	0.2429
science	-5.3882	-4.5072	0.0000
computer	2.1713	4.3525	0.0000
R-squared	0.1527		

Table 2.12: Growth regression for population for ages 55-59 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	0.2989	8.9857	0.0000
log(pop0)	-0.0217	-4.9543	0.0000
management	0.0906	0.2443	0.8071
business	0.0846	0.2109	0.8331
architecture	0.5582	1.1785	0.2394
sales	0.0302	0.0721	0.9426
arts	3.6300	3.4479	0.0006
education	-0.5255	-0.6739	0.5008
science	0.9957	0.7929	0.4284
computer	0.3556	0.6783	0.4980
R-squared	0.1141		

Table 2.13: Growth regression for population for ages 60-64 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	0.3751	10.8531	0.0000
log(pop0)	-0.0195	-4.1632	0.0000
management	1.0728	2.6796	0.0077
business	0.2284	0.5267	0.5987
architecture	0.1140	0.2222	0.8243
sales	-0.0437	-0.0959	0.9237
arts	2.3588	2.0731	0.0389
education	0.2510	0.2977	0.7661
science	3.4988	2.5698	0.0106
computer	0.5749	1.0113	0.3126
R-squared	0.1682		

Table 2.14: Growth regression for population for ages 65-69 by occupation

Variables	Coefficient	t-statistic	$t-$probability
constant	0.2279	5.9854	0.0000
log(pop0)	-0.0094	-1.7845	0.0752
management	1.1153	2.4623	0.0143
business	-1.1422	-2.3197	0.0209
architecture	0.5395	0.9260	0.3550
sales	0.3344	0.6460	0.5187
arts	1.8955	1.4705	0.1423
education	-1.6808	-1.7550	0.0801
science	6.4824	4.1876	0.0000
computer	0.7716	1.1946	0.2330
R-squared	0.1621		

Table 2.15: Growth Correlations Between Twins by Age Groups

Age Group	Twin 1	Twin 2
20-24	0.15596	0.21333
25-29	0.14737	0.19239
30-34	0.24627	0.18301
35-39	0.37750	0.23031
40-44	0.27728	0.12695
45-49	0.26415	0.22139
50-54	0.22121	0.16400
55-59	0.25546	0.18815
60-64	0.15913	0.15518
65-69	0.20555	0.16106

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VITA

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