Metropolitan Migration Flows of the Creative Class by Occupation using 3-Year 2006-2008 and 2009-2011 American Community Survey Data*

Charlynn A. Burd

Journey to Work and Migration Statistics Branch
Social, Economic, and Housing Statistics Division (SEHSD)
U.S. Census Bureau

Working Paper Number 2013-11
2013 Annual Meeting of the Association of American Geographers
Los Angeles, CA
April 9-13, 2013

* This work is released to inform interested parties of ongoing research and to encourage discussion of work in progress. Any views or opinions expressed in the paper are the authors' own and do not necessarily reflect the views or opinions of the U.S. Census Bureau. Please direct correspondence to Charlynn A. Burd, U.S. Census Bureau, SEHSD, via e-mail at charlynn.burd@census.gov.

Abstract:

The creative class is conceptualized as a highly mobile group. In the free market economic environment of the United States, the creative class has been viewed as a group who potentially could have a large economic impact on metropolitan regions. As such, the creative class is highly sought after by cities in order to encourage and promote economic development. While Florida's (2002) definition of the creative class included a broad range of creative individuals, measured by occupational categories from artists to physicists to engineers, there has been no consensus of occupations that are truly classified as creative. In addition, there has been no baseline method established that analyzes the creative class by occupation and migration simultaneously.

This research explores the relationship between migration and occupation by metropolitan areas in the United States, specifically focusing on the creative class. The American Community Survey (ACS) captures all three elements that are pertinent to this analysis, occupation, migration, and metropolitan location. The 2009-2011 3-Year ACS Estimates provide the most recent data for examining the creative class emerging from the 2008 United States recession. Previous 2006-2008 3-year data allows for a baseline dataset for comparison. This paper analyzes the migration of the creative class from 2006-2008 to 2009-2011 by selected occupations. Occupational categories continue to be used to examine the creative class (Abel *et al.* 2012), but only limitedly with regard to migration (Scott 2009). This analysis contributes to understanding migration of the creative class. There is one main question guiding this research: What are the geographic differences between migrating individuals with occupations in the creative class? In order to examine this, the current concentration of occupations based on three knowledge bases, as defined in Asheim and Hansen (2009) are identified.

Background

The creative class is viewed as a highly mobile group. The group's perceived mobility has allowed for metropolitan areas to develop urban planning and economic strategies to attract talented individuals to help improve their economic prowess and continue to improve competitiveness. Previous research has identified the creative class as those individuals whose occupation has elements of creativity and skill (Florida 2012). However, one criticism with the thesis of the creative class is that the occupational approach is too broad and captures a large portion of the workforce that may not be creative. Recent research has attempted to address this criticism.

Asheim and Hansen (2009) proposed a tripartite approach to conceptualizing the creative class. They proposed that the creative class be deconstructed into three distinct knowledge bases. Figure 1 illustrates the three knowledge bases with regard to Florida's definition of people and business climates. Other researchers have varied their definitions of creative workers (Markusen *et al.* 2008, Scott 2009, Abel *et al.* 2012, Mellander and Florida 2012). Refining the definition of the creative class allows for comparison among the different groups of occupation in order to determine the degree of similarity or difference. This paper employs the knowledge-base framework of Asheim and Hansen (2009) in order to examine the migration behavior of the creative class.

The main objective of this paper is to explore the migration behavior of the creative class, using an occupational approach, pre- and post- 2008 recession. In order to accomplish this, the paper is divided in two sections. The first section emphasizes and describes the demographic characteristics of the creative class. In order to discern the impact of the recession a description of the creative class cohort is paramount. Section 1 relies on data from the Census 2000 long form. Additionally, data used here is from the American Community Survey (ACS). The ACS is a continuous survey that provides yearly data for information on the population of the United States, which aids in providing communities with information necessary to plan for investments and services.[1] Section 1 also presents 2007-2011 5-year estimates for selected characteristics of the creative class. The analysis in Section 2 relies upon two 3-year ACS estimates (2006-2008

[1] Source: U.S. Census Bureau, "About the American Community Survey", www.census.gov/acs/www/about_the_survey/american_community_survey/

and 2009-2011). The break in the two datasets allows for analysis that illustrates pre- and post-recession periods.

Data

There are three datasets utilized in this analysis. First, Census 2000 data are used to construct a baseline for the creative class by knowledge base. For a point of comparison, 2007-2011 5-year estimates are included. Benetsky and Koerber (2012) maintain that there is congruence between the two surveys. Even though the two surveys ask different migration questions with a different time period estimates from each survey are considered comparable to one another.[2] Finally, 3-year estimates (2006-2008 and 2009-2011) are analyzed. These two datasets have large samples that span six years of population movement with a clear divide in 2008. The 3-year and 5-year estimates are multiyear combinations of the 1-year records with appropriate adjustments to the weights and inflation adjustment factors.[3]

Definitions

Migrants are identified as persons age 1 year or older who had a different residence 1 year ago. The ACS identifies movers and non-movers. This paper delineated three different types of moves. First, migrants were identified as movers based on their place of residence. The first type of mover is an intramover or an individual who has moved within the same Core Based Statistical Area (CBSA). An intramove is conceptualized as a short distance move and may not necessarily carry the same decisions or factors required of a long distance move. The second type of mover is an intermover. These movers had a different residence 1 year ago and were not living in the same CBSA as last year. Intermovers are moving from one CBSA to another CBSA and have to overcome some distance friction. The intermetropolitan movers include individuals that moved between two CBSAs, as well as those who previously resided in areas of the United States that were not in CBSA areas. Finally, the third category of movers are those from abroad. Movers from abroad are defined in this research as individuals who previously resided in a different country one year ago not including military personnel. However, it may capture some

[2] Census 2000 asked respondents where the person lived five years ago, while the ACS asks where respondents lived one year ago. The one year change is a reflection on the on-going data collection of the ACS.
[3] http://www.census.gov/acs/www/Downloads/data_documentation/Accuracy/MultiyearACSAccuracyofData2011.pdf

non-military migrants in the same household as military service member who moved for military reasons. This paper focuses on movers and contributes to improved understanding of migration patterns of the creative class in the United States.

Previous research has identified the creative class as individuals whose occupation has elements of creativity and skill (Florida 2012). Researchers have varied their definitions of creative workers (Markusen *et al.* 2008, Scott 2009, Abel *et al.* 2012, Mellander and Florida 2012). While Florida offers an occupational approach to identifying the creative class, Asheim and Hansen (2009) suggest a knowledge-base approach to analysis which relies on both industry and occupation, and is helpful for fully exploring the role the creative class has in a metropolitan or urban economic milieu. A proposed knowledge-base approach has been suggested in order to refine and explore the creative class (Asheim and Hansen 2009).

Therefore, this paper uses occupation, defined by Census Occupation Codes, identified in Table 1, to delineate three distinct knowledge bases: Analytic, Synthetic, Symbolic. Knowledge bases are categorized based on business and people climates. Figure 1 illustrates the three knowledge bases with regard to people and business climates as suggested by Asheim and Hansen (2009). Table 1, Proposed Knowledge Bases for the Creative Class by Occupation, notes three knowledge bases and the occupations included in each group. For example, photographers are included in the symbolic group, while engineers are in the synthetic group.

Prior to age 25, many individuals move frequently.[4] For the older threshold, persons age 64 or younger are expected to still be participating in the workforce. This analysis includes individuals aged 25 – 64 who are employed and are not military personnel.[5]

This analysis relies on the Core Based Statistical Area (CBSA) as the main geography. The geographic subdivision refers to Metropolitan and Micropolitan Statistical Areas.[6] Defined by the Office of Management and Budget (OMB), the delineated areas serve as a proxy for a functional urban area. In 2008, there were 933 CBSAs. The CBSA is an intermediary

[4] This is often related to educational pursuits or entry into the workforce after finishing education.
[5] The analysis excludes unemployed, armed forces at work, armed forces, not at work, and not in the labor force.
[6] The county or counties or equivalent entities associated with at least one core (urbanized area or urban cluster) of at least 10,000 population, plus adjacent counties having a high degree of social and economic integration with the core as measured through commuting ties with the counties associated with the core.
<http://factfinder2.census.gov/help/en/glossary/c/core_based_statistical_area_cbsa_.htm>

geographic scale; spatially, it is smaller than states, yet larger than counties. This unique geography also allows for urban areas to cross state boundaries thus yielding a more accurate representation of urban market approximation.

The analysis presented here used 3-year ACS estimates. The Census Bureau examined domestic migration flows using 2005 1-year ACS estimates. Koerber (2007) reports that the forthcoming three- and five-year estimates can provide less variance and smaller geographies than state to state flows. Three-year datasets provide a larger sample size, more precision, and smaller geographies for analysis than 1-year datasets.[7]

Results

Descriptive Analysis Census 2000 and 2007-2011 5-year ACS

In order to establish the baseline of the creative class, data from the 2000 Decennial Census long form were used. In 2000, 64.9 percent of individuals age 25-39 identified as movers whereas 34.1were nonmovers (Franklin 2003). Figure 2 notes the total number of individuals and their respective mover or non-mover status (Franklin 2003). The population ages 40-64 were a majority nonmovers (65.8 percent) while 34.2 percent of the total population were movers (Franklin 2003). This previous report provides an age baseline to compare the creative class to total population in terms of migration status. Figure 3 presents the total number of individuals with comparable occupations in the creative class. Additionally, Figure 3 includes the total number of creative class individual migrants, who were employed and are non-military, who resided at a different address 5 years ago. In 2000, 39.5 percent of individuals ages 25-39 indicated they were in the same residence (nonmovers) five years earlier while 60.5 percent were in a different location. Figure 2 also illustrates that 71 percent of creative class members ages 40-64 were nonmovers while 29 percent had moved in the past 5 years. Creative class movers ages 25-39 are more likely to be in a different residence the previous year.

The most current 5-year dataset is the 2007-2011 ACS. The creative class has approximately 7.9 million people in the three knowledge bases. Figure 4 highlights the 5-year ACS 2007-2011 estimates for the creative class by movers and nonmovers. The synthetic

[7] Documentation of the distinguishing features of ACS 1-year, 3-year, and 5-year estimates.
< http://www.census.gov/acs/www/guidance_for_data_users/estimates/>

knowledge base had the highest percentage of nonmovers (12.4 percent were movers) for each particular knowledge base. The analytic category had the most movers from among the three knowledge bases (613,251).

Figure 5 compares estimates for four groups of movers, three creative class knowledge bases and all other occupations. The creative class, as a whole, follows the trend of decreasing numbers of movers as age increases. This parallels the migration trends for other knowledge bases. The five-year data for the creative class knowledge bases parallels life course migration patterns which indicates the most mobile population are individuals in their 20s. As people age, migration rates tend to decrease.

The creative class migrating from abroad comes from two principle world regions, Europe (14,313) and Asia (38,035) as illustrated in Figure 6. However, most creative class members, approximately 94 percent, during this time had a previous residence within the United States regardless of knowledge base. This suggests that most migration occurs with in the United States, not from abroad.

The racial composition of the creative class mover, shown in Figure 7, is 69.8 percent white alone. Figure 8, illustrates that regardless of the particular knowledge base, the creative class mover is predominantly non-Hispanic (96.1 percent). The demographic composition of the creative class and the creative class mover is important to understanding potential motivations for migration. While 5-year ACS data is comparable to 2000 Census data, the aggregation over five years does not allow for comparison before and after the recession. The 3-year data provides the needed break to examine migration trends between pre- and post-recession.

Pre- and Post-Recession Analysis 2006-2008 and 2009-2011 3-year ACS

The second portion of this research attempts to analyze the pre-recession and post-recession migration of the creative class with a focus on the net gains and losses for CBSAs throughout the U.S. In order to compare underlying trends, the 2006-2008 and 2009-2011 3-year ACS datasets are examined. First, the net migration of the creative class is explored. Table 2 presents selected CBSAs and their respective creative class net migration. All three knowledge bases are included in Table 2. The 2006-2008 estimates suggest that Washington, Houston, Boston, Seattle, San Francisco, New York and Dallas were among the highest CBSAs with a net gain of creative class individuals. However, there is not a statistically significant difference among the selected estimates in 2006-2008. The 2009-2011 estimates suggest that Washington, D.C., was the highest net gainer of creative class individuals. Among the other top ranking CBSA net gainers for creative class individuals in 2009-2011 are Houston, Boston, and San Jose. Not every CBSA estimate differs between the two 3-year samples. Table 2 highlights examples of the differences in estimates from the two 3-year samples. Of the twenty selected CBSAs, four metros had estimates that were statistically different between the two periods. Only Washington, D.C. had a net increase of the creative class population. The aggregate population estimates presented in Table 2 can mask what is occurring among the three distinct knowledge bases.

Table 3 disaggregated the net migration of the creative class by knowledge base. This provides a more nuanced presentation of the patterns of the creative class. Only three CBSAs, San Francisco, Atlanta, and Seattle, from among the seven net analytic population gainers were statistically different (Table 3). All three had lower net population in 2009-2011 than in the previous period. Among the selected nets for the synthetic knowledge base presented in Table 3, Seattle, Washington, and Boston were statistically different in between the two periods. However, Seattle's net migration decreased from 2006-2008 to 2009-2011 while Washington, D.C. and Boston increased. Among the selected CBSAs in the symbolic knowledge base, Portland and Washington, D.C. had a statistically significant difference between 2006-2008 and 2009-2011 (Table 3). Net synthetic knowledge base movers to Portland decreased, while Washington, D.C. increased.

In the post-recession period of 2009-2011, only Washington, D.C. had a statistically different net creative class gain compared to other CBSAs among the selected analytic knowledge base gainers. Examining net population gains and losses presents an individual metropolitan perspective. In order to present a comprehensive analysis on other migration types, intrametropolitan moves and intermetropolitan flows, are considered.

Migration Flows

Thus far, migration has only been discussed by examining the destinations of migrants. However, a more comprehensive approach also considers origins. Intrametropolitan moves are the moves where the respondents' previous residence one year ago was in the same CBSA.

These are short distance moves. Among the selected analytic CBSAs Washington, D.C., Los Angeles, San Francisco, and Seattle, all increased in their respective intrametropolitan movement. In the selected synthetic subgroup, the number of intrametropolitan movers increased in two CBSAs, Los Angeles and Houston, between the two periods. In the selected symbolic knowledge base, three CBSAs, Los Angeles, Miami, and San Francisco, had increases between the two periods.

Intermetropolitan flows by knowledge base are numerically small flows. Table 4 highlights selected CBSAs with respect to their intermigration. It should be noted that these flows are not paired net flows; only the individual paired flow is analyzed. For example, the flow from Washington, D.C. to Baltimore is estimated to be 1,411 people.[8] However, the flow from Baltimore to Washington, D.C. is estimated to be 985 people. This would yield a net paired flow to Washington, D.C. from Baltimore of 426 people in the analytic knowledge base. Throughout this section, it is noticeable that many of the inflows are reciprocal and have a degree of adjacency. Even though a move from Washington, D.C. to Baltimore is an intermetropolitan move, it is still a relatively short distance. This finding holds true for flows in 2009-2011. Among the selected flows for analytic knowledge base, four of the flows were between two adjacent CBSAs. While none of the flows was significantly different from one another, adjacency appears to be a main theme.

The symbolic knowledge base has one flow among the selected flows that was different from the other flows: New York to Los Angeles. This flow was among those presented in 2006-2008 and remains in 2009-2011. Considering the composition of occupations in the group is predominantly artists, this finding is expected. Finally, the flows between CBSAs by knowledge base were calculated; Tables 7-9 represent information from Tables 4-5, but also provide a significance test between estimates for the two periods. Among the flows presented for each period, three CBSAs, Washington, D.C. to Baltimore, Baltimore to Washington, D.C., and San Francisco to San Jose, were in both periods. However, only three flows San Jose to San Francisco, Philadelphia to New York, and Los Angeles to Riverside were not. Between the two periods from among the selected analytic knowledge base, San Jose had an increase in movers.

[8] The estimates for the Washington to Baltimore flow and the Baltimore to Washington flow are not statistically different.

Table 8 presents selected intermetropolitan flows for the synthetic knowledge base. Synthetic flows between CBSAs in both periods were the same. While none of the flows was different from one another, two flows were different between the periods. San Francisco to San Jose increased from 343 to 840. The flow from Detroit to Seattle had 319 movers in 2006-2008, but no flow in 2009-2011 and the estimate is different between the two periods. Only San Francisco had an increase from 2006-2008 and 2009-2011. Additionally, from among the select flows, five of the six have a degree of adjacency.

Table 9 presents selected intermetropolitan flows for the symbolic knowledge base. The symbolic knowledge base intermetropolitan migration pattern contrasts the analytic and synthetic. There was only one intermetropolitan flow from among the selected in both periods, New York to Los Angeles. While this flow was repeated, it was not different from the other flows in each period, nor was it statistically different from 2006-2008 to 2009-2011. However, among each of the presented CBSA flows identified, only three were different between the two periods, and only one had a degree of adjacency, Los Angeles to Riverside. While much of the research focuses on the intermetropolitan migration, many more moves occur within the same metro area.

Summary

In summary, the 5-year ACS 2007-2011 suggests that the younger the age, the more movers there are regardless of knowledge base. In this way, the creative class parallels the total population. In the post-recession period of 2009-2011, only Washington, D.C. had a statistically different net creative class gain (Table 2). Intrametropolitan moves are more prevalent than intermetropolitan moves. Among the selected CBSAs for analytic knowledge base, there was an increase in the number of intrametropolitan movers between 2006-2008 and 2009-2011 (Table 6). In an economic recession, it is expected that people would be less likely to move, however, the increase in moves between the two periods may suggest that people were moving to cheaper housing in the same metropolitan areas. Among the selected CBSAs for synthetic knowledge base intrametropolitan movers, Los Angeles and Houston had an increase between 2006-2008 and 2009-2011. New York and Los Angeles were among the selected CBSAs for intrametropolitan movers in the symbolic group. There was an increase of intrametropolitan movers in Los Angeles between the two periods. Intrametropolitan mobility has been overlooked in the literature with respect to the creative class. While intrametropolitan moves increased in the post-recession period for some knowledge bases in some metropolitan areas, some metropolitan areas did not have a significant difference between the two periods. While intrametropolitan moves or short distance moves are the most common type, long distance intermetropolitan moves of the creative class were also considered in this paper.

A central narrative presented in literature is that the creative class moves to new cities thus producing a new work force that can be energized to aid the economic development of a place. The intermetropolitan moves differ between the three knowledge bases and between the two periods. This paper suggests that most mobility, creative or for the total population is found at the local or intrametropolitan scale rather than the intermetropolitan scale. Intermetropolitan flows, at least in these two periods, exhibit characteristics of adjacency. Washington, D.C. to Baltimore was among the selected flows for the analytic knowledge base that exhibits the adjacency finding. San Francisco to San Jose exemplifies this from the CBSAs presented in Table 8. While there is still the element of adjacency in the symbolic knowledge base flows, generally the flows presented in Table 9 are longer distances, such as New York to Los Angeles and Los Angeles to New York.

While it is clear that intrametropolitan migration is greater than intermetropolitan migration for the two periods, this study did not address the demographic characteristics of each group. Future work needs to incorporate not only the flow, but also demographic characteristics. Are the intrametropolitan movers the same as intermetropolitan movers? An additional direction for future research would be to consider the size of the origin and destination of metropolitan area. Does the creative class migrate up, down, or laterally across the U.S. urban hierarchy? Does the movement depend on the respective knowledge base? The top ranked flows considered in this work reflects the magnitude of the flow, not the size of the origin or destination. How do revised OMB definitions affect the results if at all? How would expanding the occupational categories to mirror other creative class studies change results? Given the overall period of reduced migration in the U.S., what are the implications for the creative class? Understanding the migration of the creative class is necessary considering the ancillary impacts to both origins and destinations with regard to metropolitan planning, services, and economic development.

References

Abel, J. R., T. M. Gabe & K. Stolarick. 2012. Workforce Skills across the Urban-Rural Hierarchy. In *Federal Reserve Bank of New York Staff Report*, 1-26. New York City: Federal Reserve Bank of New York.

Asheim, B. & H. K. Hansen (2009) Knowledge Bases, Talents, and Contexts: On the Usefulness of the Creative Class Approach in Sweden. *Economic Geography,* 85**,** 425-442.

Benetsky, M. a. W. K. 2012. How do the ACS five-year migration data compare to the 2000 Census migration data? In *Annual Meeting of the Population Association of America,* 16. San Francisco.

Florida, R. (2002) The rise of the creative class: and how it's transforming work, leisure, community and everyday life. *New York: Basic*.

---. 2012. *The Rise of the Creative Class--Revisited: --Revised and Expanded*. Basic books.

Franklin, R. 2003. Migration of the Young, Single and College Educated: 1995 to 2000. In *Census 2000 Special Reports*. Washington, DC: U.S. Census Bureau.

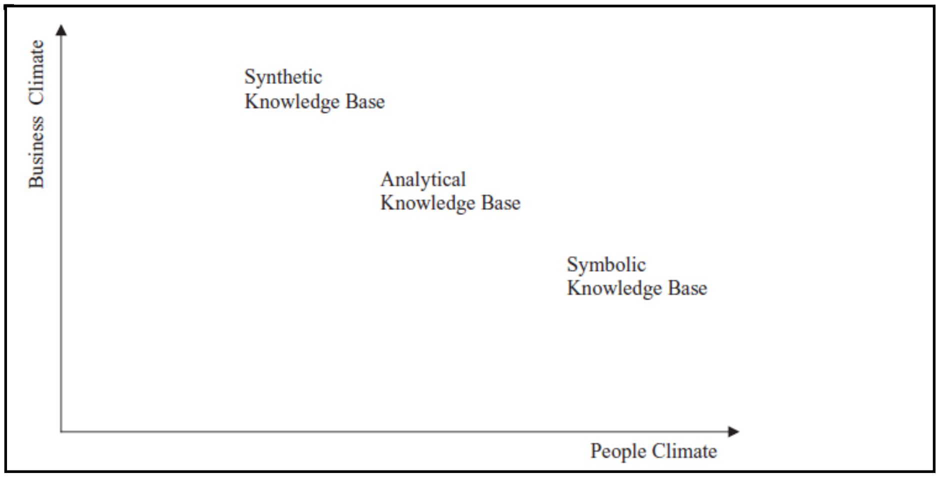
Koerber, W. 2007. Domestic Migration Flows for States from the 2005 ACS. In *Annual Meeting of the Population Associtation of America*. New York City.

Markusen, A., G. H. Wassall, D. DeNatale & R. Cohen (2008) Defining the Creative Economy: Industry and Occupational Approaches. *Economic Development Quarterly,* 22**,** 24-45.

Mellander, C. & R. Florida. 2012. The Rise of Skills: Human Capital, the Creative Class and Regional Development. Royal Institute of Technology, CESIS-Centre of Excellence for Science and Innovation Studies.

Scott, A. J. (2009) Jobs or amenities? Destination choices of migrant engineers in the USA*. *Papers in Regional Science,* 89**,** 43-63.

Figure 1. Proposed Knowledge Bases for the Creative Class

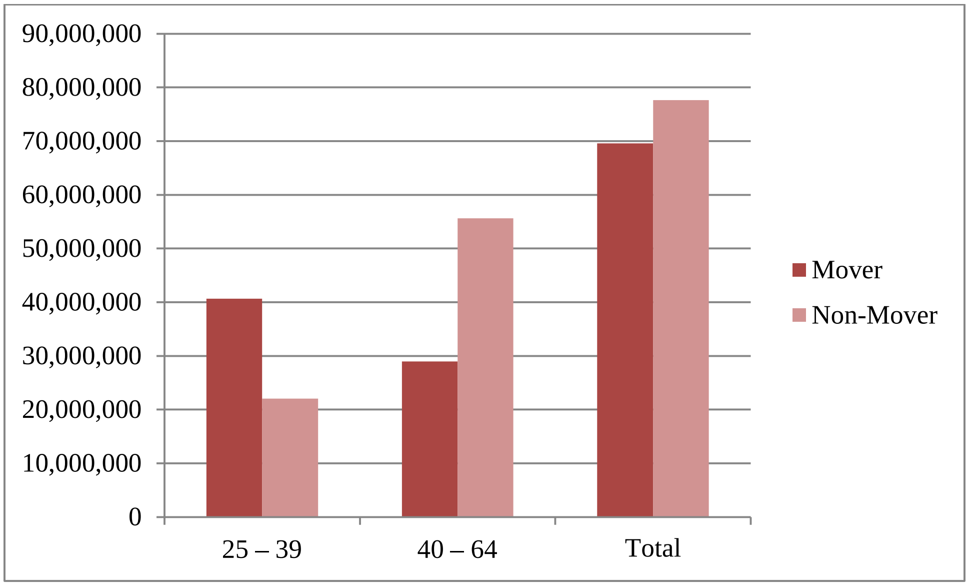


Source: Asheim and Hansen 2009, 431

Table 1: Proposed Knowledge Bases for the Creative Class by Occupation

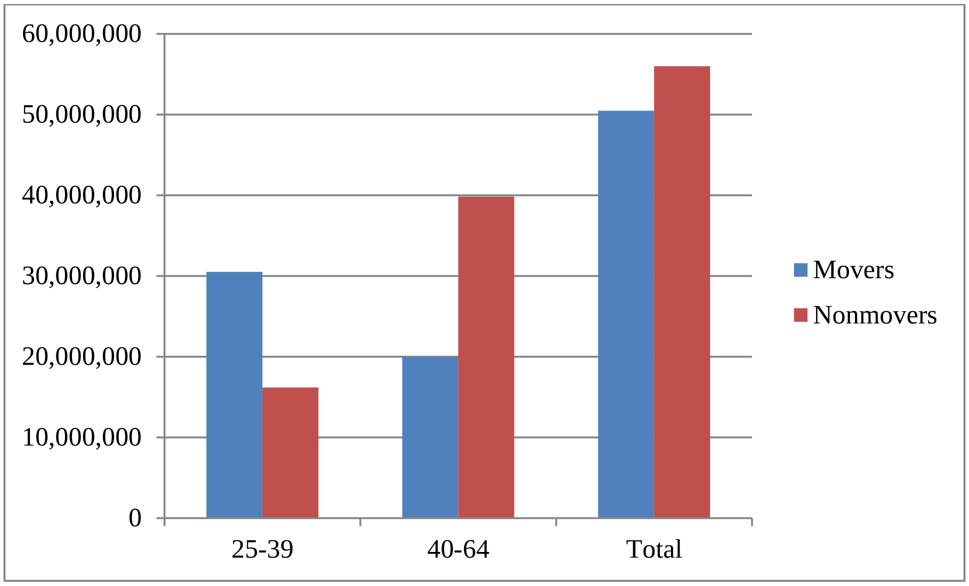
Analytic Agricultural and Food Scientists (1600); Biological Scientists (1610); Conservation Scientists and Foresters (1640); Life Scientists, All Other (1660); Astronomers & Physicists (1700); Atmospheric & Space Scientists (1710); Chemists & Materials Scientists (1720); Environmental Scientists & Geoscientists (1740); Physical Scientists, All Other (1760); Economists (1800); Survey Researchers (1815); Psychologists (1820); Sociologists (1830); Urban & Regional Planners (1840); Miscellaneous Social Scientists & Related Workers (1860); Social Science Research Assistants (1950); Computer & Information Research Scientists (1005); Computer Systems Analysts (1006); Information Security Analysts (1007); Computer Programmers (1010); Software Developers, Applications & Systems Software (1020); Web Developers (1030); Computer Support Specialists (1050); Database Administrators (1060); Network & Computer Systems Administrators (1105); Computer Network Architects (1106); Computer Occupations, All Other (1107); Mathematicians (1210); Operations Research Analysts (1220); Statisticians (1230); Miscellaneous Mathematical Science Occupations (1240) Synthetic Architects, Except Naval (1300); Surveyors, Cartographers, & Photogrammetrists (1310); Aerospace Engineers (1320); Agricultural Engineers (1330); Biomedical Engineers (1340); Chemical Engineers (1350); Civil Engineers (1360); Computer Hardware Engineers (1400); Electrical and Electronics Engineers (1410); Environmental Engineers (1420); Industrial engineers Including Health & Safety (1430); Marine Engineers & Naval Architects(1440); Materials Engineers (1450); Mechanical Engineers (1460); Mining & Geological Engineers Including Mining Safety Engineers (1500); Nuclear Engineers (1510); Petroleum Engineers (1520); Engineers, All Other (1530) Symbolic Artists and related workers (2600); Designers (2630); Actors (2700); Producers & Directors (2710); Dancers & Choreographers (2740); Musicians, Singers, and Related Workers (2750); Entertainers, Performers, Sports & Related Workers, All Other (2760); Editors (2830); Technical Writers (2840); Writers & Authors (2850); Broadcast and Sound Engineering Technicians & Radio Operators (2900); Photographers(2910); Television, Video, & Motion Picture Camera Operators & Editors (2920); Media and Communication Equipment Workers, All Other (2960); and Chefs and Head Cooks (4000)

Figure 2: Census 2000 Age Characteristics for Total Population



Source: Type of Move by Age Group: 1995-2000 (Franklin 2003)
http://www.census.gov/prod/2003pubs/censr-12.pdf

Figure 3: Census 2000 Age Characteristics for Creative Class

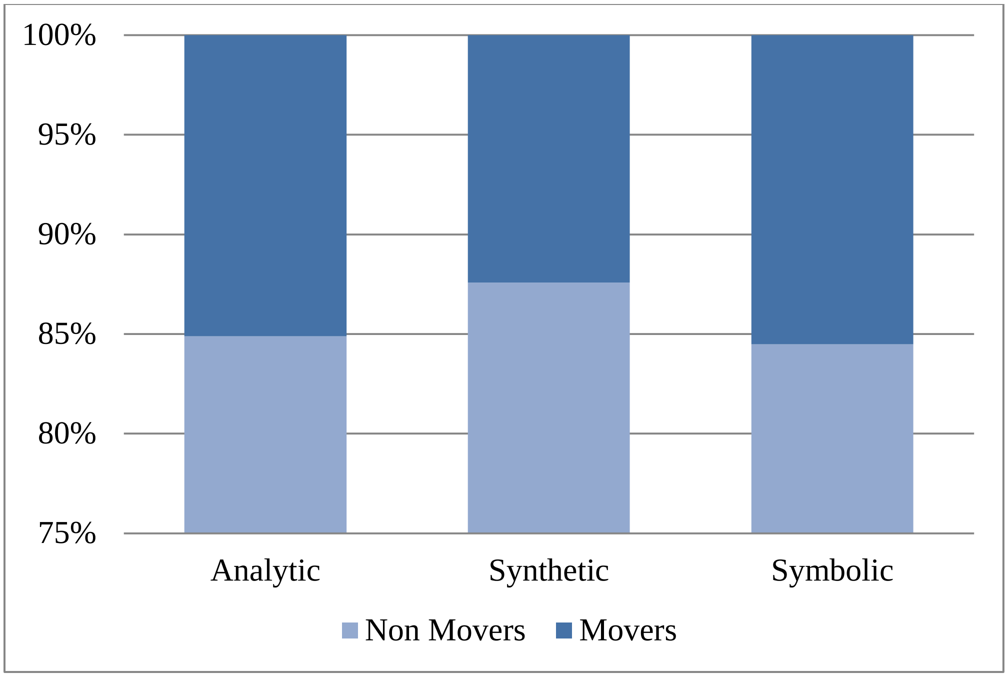


Source: Census 2000 Long Form data. For more information, see http://www.census.gov/prod/cen2000/doc/sf3.pdf.

Note: The margin of error for Census 2000 estimates were computed using a design factor of 1.1 in accordance with Chapter 8 of the Summary File 3, 2000 Census of Population and Housing: Technical Documentation, issued July 2007. See technical documentation for further information at http://www.census.gov/prod/cen2000/doc/sf3.pdf.

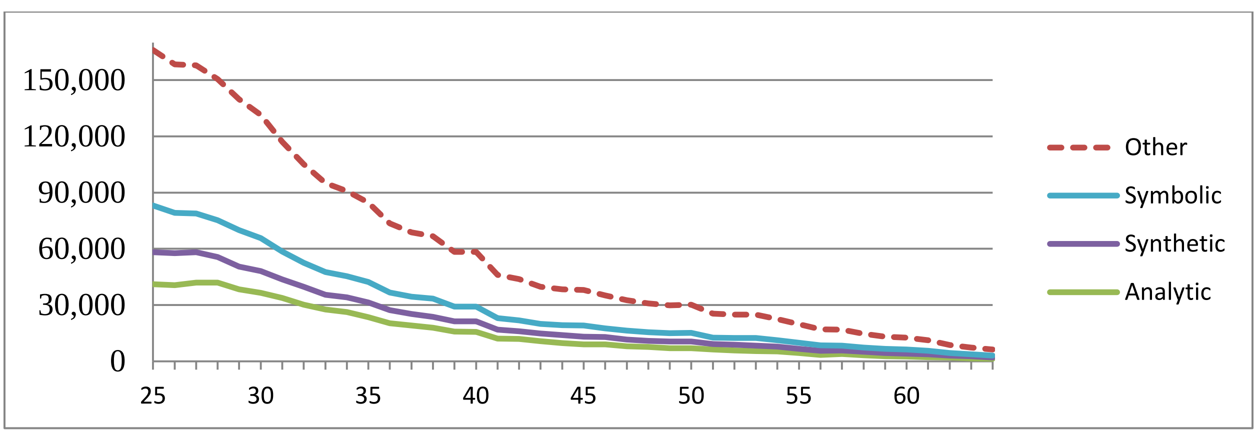
Note: Occupation Codes used in Census long form to construct Creative Class:
Analytic:160;161;164;165;170;171;172;174;176;180;181;182;183;184;186;196;100;101;102;110;111;121;104;106;
121;122;123;124
Synthetic: 130;131;132;133;134;135;136;140;141;142;143;144;145;146;150;151;152;153
Symbolic: 260;263;270;271;274;275;276;283;284;285;290;291;292;296;400

Figure 4: 5-year ACS (2007-2011) Creative Class by Migration Status



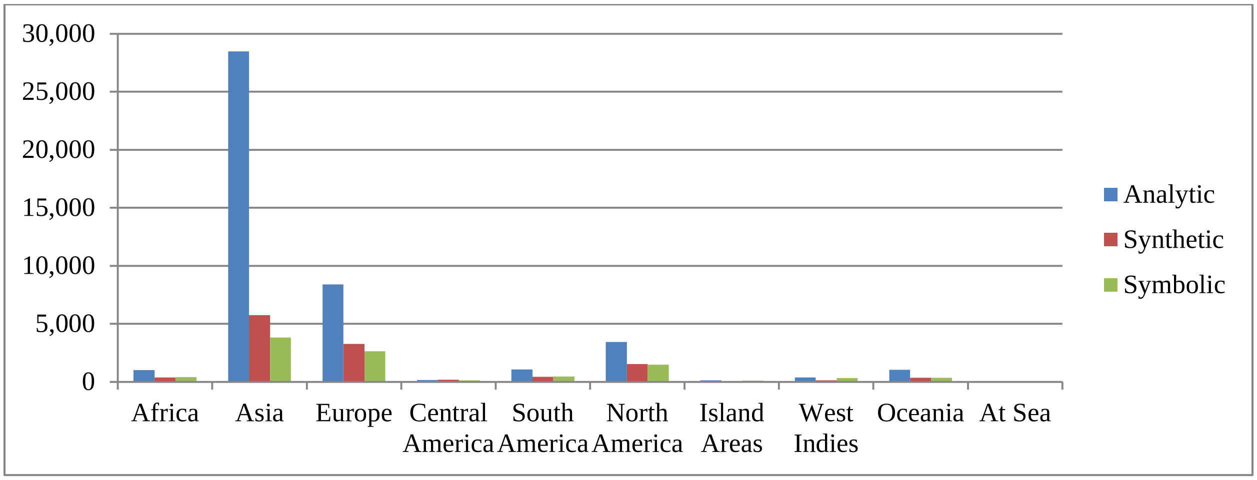
Source: American Community Survey 2007-20115-year data. For more information, see http://www.census.gov/acs

Figure 5: 5-year ACS (2007-2011) Comparison of Movers and Respective Knowledge Bases by Age



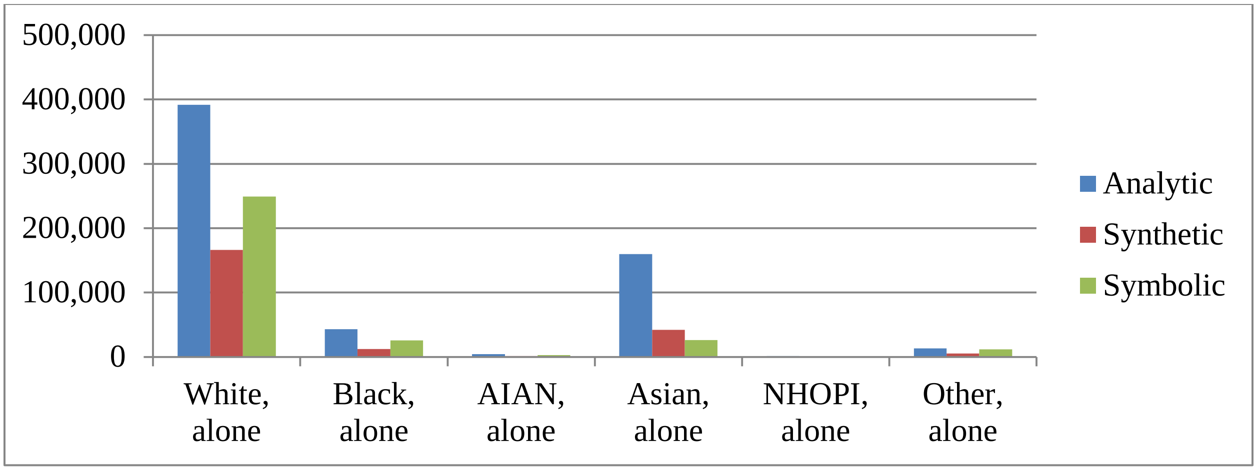
Source: American Community Survey 2007-20115-year data. For more information, see http://www.census.gov/acs

Figure 6: 5-year ACS (2007-2011) Abroad Movers and Knowledge Base



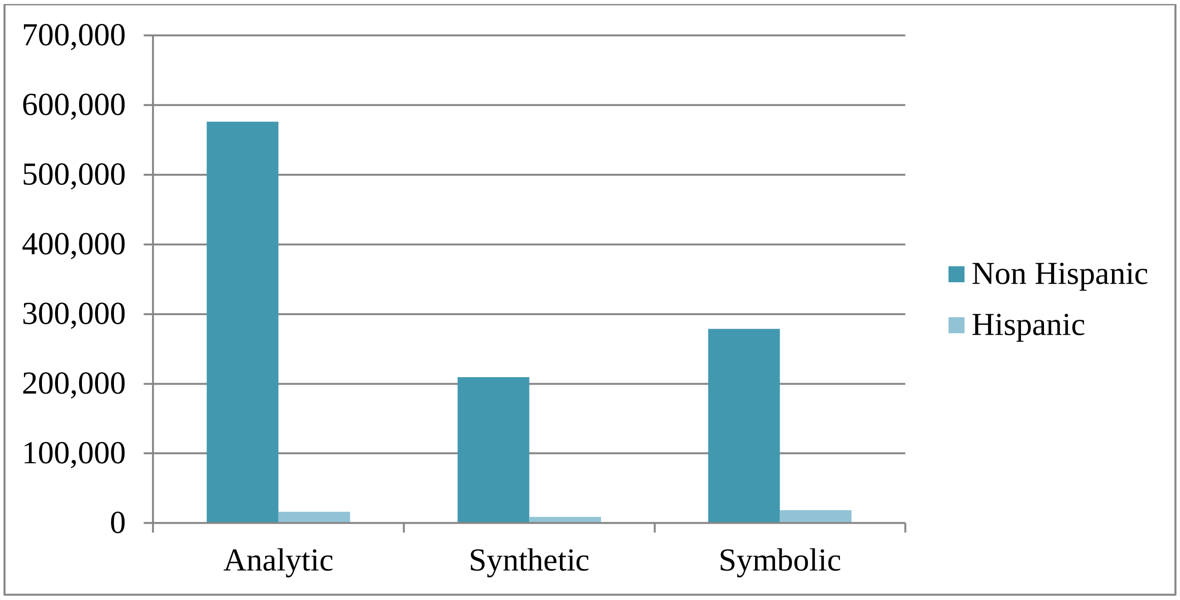
Source: American Community Survey 2007-20115-year data. For more information, see
http://www.census.gov/acs

Figure 7: 5-year ACS (2007-2011) Racial Composition of Movers in the Creative Class



Source: American Community Survey 2007-20115-year data. For more information, see http://www.census.gov/acs

Figure 8: 5-year ACS (2007-2011) Comparison of Hispanic versus Non-Hispanic Composition of Movers in the Creative Class



Source: American Community Survey 2007-20115-year data. For more information, see http://www.census.gov/acs

Table 2: Selected CBSAs with Among the Highest Net Creative Class Migration 2006-2008 & 2009-2011

	2006-2008		2009-2011		Significantly Different
CBSA	Estimate	MOE	Estimate	MOE	
Washington-Arlington-Alexandria	4,596	1,784	8,227	2,144	Yes
Houston-Sugar Land-Baytown	4,297	1,261	5,385	1,541	No
Boston-Cambridge-Quincy	3,251	1,452	3,712	1,378	No
San Jose- Sunnyvale-Santa Clara	3,240	1,079	3,739	1,594	No
Los Angeles-Long Beach-Santa Ana	986	1,959	2,811	1,774	No
Dallas-Fort Worth-Arlington	4,230	1,354	4,021	1,590	No
San Francisco-Oakland-Fremont	4,939	1,587	2,614	1,833	No
Seattle-Tacoma-Bellevue	5,733	1,290	2,709	1,441	Yes
Portland-Vancouver-Hillsboro	3,162	865	1,829	1,064	No
New York-Northern New Jersey-Long Island	4,096	2,441	3,978	2,275	No
Atlanta-Sandy Springs-Marietta	3,490	1,170	1,181	1,397	Yes
Austin-Round Rock-San Marcos	2,988	1,147	1,964	1,024	No
Denver-Aurora-Broomfield	1,710	1,153	1,977	990	No
Las Vegas-Paradise	1,599	685	386	672	Yes
Phoenix-Mesa-Glendale	2,066	1,215	1,418	1,269	No
Charlotte-Gastonia-Rock Hill	2,003	683	1,345	707	No
San Antonio-New Braunfels	1,268	675	1,552	813	No
Baltimore-Towson	1,308	1,017	1,637	1,086	No
Riverside-San Bernardino-Ontario	842	904	1,733	871	No
Philadelphia-Camden-Wilmington	1,325	1,301	759	1,227	No

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

Table 3: Selected CBSAs with Among the Highest Creative Class Migration by Knowledge Base 2006-2008 & 2009-2011

		2006-2008		2009-2011		Statistically Different
	CBSA	Estimate	MOE	Estimate	MOE	
Analytic	Washington-Arlington-Alexandria	4,397	1,465	5,278	1,619	No
	San Francisco-Oakland-Fremont	4,175	1,259	2,080	1,283	Yes
	Seattle-Tacoma-Bellevue	4,114	928	2,122	1,031	Yes
	New York-Northern New Jersey-Long Island	3,580	1,487	2,994	1,541	No
	Atlanta-Sandy Springs-Marietta	3,081	888	1,041	1,065	Yes
	San Jose-Sunnyvale-Santa Clara	2,184	927	3,260	1,312	No
	Houston-Sugar Land-Baytown	1,642	918	2,428	1,186	No
	CBSA	Estimate	MOE	Estimate	MOE	
Synthetic	Houston-Sugar Land-Baytown	2,617	773	2,689	782	No
	Seattle-Tacoma-Bellevue	1,434	658	172	543	Yes
	Dallas-Fort Worth-Arlington	1,205	767	845	935	No
	San Jose-Sunnyvale-Santa Clara	1,094	440	816	648	No
	San Diego-Carlsbad-San Marcos	912	414	283	541	No
	Washington-Arlington-Alexandria	207	648	1,698	796	Yes
	Boston-Cambridge-Quincy	143	571	1,066	547	Yes
	CBSA	Estimate	MOE			
Symbolic	Austin-Round Rock-San Marcos	1,002	606	922	488	No
	Las Vegas – Paradise	909	598	198	405	No
	Portland-Vancouver-Hillsboro	889	382	88	397	Yes
	Los Angeles-Long Beach-Santa Ana	830	1,233	2,052	1,104	No
	New York-Northern New Jersey-Long Island	771	1,367	1,744	1,283	No
	Washington-Arlington-Alexandria	-8	621	1251	719	Yes
	Dallas-Fort Worth-Arlington	562	571	979	745	No

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

Table 4: Selected CBSAs with Among the Highest Creative Class Migration by Knowledge Base 3-Year 2006-2008 ACS (Inter CBSA Moves[9])

Analytic			
From CBSA	To CBSA	Estimate	MOE
Washington-Arlington-Alexandria	Baltimore-Towson	1,411	360
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	1,312	355
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	1,303	314
Baltimore-Towson	Washington-Arlington-Alexandria	985	337
Philadelphia-Camden-Wilmington	New York-Northern New Jersey-Long Island	928	573
Synthetic			
From CBSA	To CBSA	Estimate	MOE
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	656	369
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	392	177
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	343	198
Detroit-Warren-Livonia	Seattle-Tacoma-Bellevue	319	212
New York-Northern New Jersey-Long Island	Philadelphia-Camden-Wilmington	309	200
Symbolic			
From CBSA	To CBSA	Estimate	MOE
New York-Northern New Jersey-Long Island	Los Angeles-Long Beach-Santa Ana	780	321
Los Angeles-Long Beach-Santa Ana	New York-Northern New Jersey-Long Island	702	418
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	518	183
New York-Northern New Jersey-Long Island	Miami-Fort Lauderdale-Pompano Beach	460	211
Boston-Cambridge-Quincy	New York-Northern New Jersey-Long Island	450	246

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

[9] Excludes movers from abroad and intrametropolitan moves.

Table 5: Selected CBSAs with Among the Highest Creative Class Migration by Knowledge Base 3-Year 2009-2011 ACS (Inter CBSA Moves[10])

Analytic			
From CBSA	To CBSA	Estimate	MOE
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	2,176	398
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	1,541	404
Washington-Arlington-Alexandria	Baltimore-Towson	1,379	456
Baltimore-Towson	Washington-Arlington-Alexandria	852	284
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	739	272
Synthetic			
From CBSA	To CBSA	Estimate	MOE
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	840	283
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	688	283
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	536	218
New York-Northern New Jersey-Long Island	Philadelphia-Camden-Wilmington	330	280
New York-Northern New Jersey-Long Island	Poughkeepsie-Newburgh-Middletown	257	232
Symbolic			
From CBSA	To CBSA	Estimate	MOE
New York-Northern New Jersey-Long Island	Los Angeles-Long Beach-Santa Ana	1,090	399
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	652	295
New York-Northern New Jersey-Long Island	Philadelphia-Camden-Wilmington	605	287
San Francisco-Oakland-Freemont	Los Angeles-Long Beach-Santa Ana	501	316
Miami-Fort Lauderdale-Pompano Beach	New York-Northern New Jersey-Long Island	369	196

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

[10] Excludes movers from abroad and intrametropolitan moves.

Table 6: Selected CBSAs with Among the Highest Creative Class Migration by Knowledge Base 3-Year 2006-2008 & 2009-2011ACS (Intrametropolitan CBSA Moves[11])

		2006-2008		2009-2011		Statistically Different
	CBSA	Estimate	MOE	Estimate	MOE	
Analytic	New York-Northern New Jersey-Long Island	28,362	1,928	29,572	1,908	No
	Washington-Arlington-Alexandria	20,625	1,428	25,273	1,760	Yes
	Los Angeles-Long Beach-Santa Ana	15,652	1,115	20,118	1,427	Yes
	Chicago-Joliet-Naperville	14,804	1,100	13,926	1,140	No
	Boston-Cambridge-Quincy	13,859	1,283	14,750	1,307	No
	San Francisco-Oakton-Fremont	12,236	1,192	15,430	1,243	Yes
	Seattle-Tacoma-Bellevue	11,412	1,086	13,765	1,306	Yes
	CBSA	Estimate	MOE	Estimate	MOE	
Synthetic	Los Angeles-Long Beach-Santa Ana	6,744	770	9,316	980	Yes
	New York-Northern New Jersey-Long Island	6,388	758	6,280	872	No
	Houston-Sugar Land-Baytown	5,046	661	6,592	963	Yes
	Dallas-Fort Worth-Arlington	4,406	686	4,393	735	No
	Washington-Arlington-Alexandria	4,393	645	5,050	806	No
	San Jose-Sunnyvale-Santa Clara	3,660	500	4,509	767	No
	CBSA	Estimate	MOE	Estimate	MOE	
Symbolic	New York-Northern New Jersey-Long Island	26,000	1,885	26,664	1,836	No
	Los Angeles-Long Beach-Santa Ana	23,471	1,821	28,222	1,762	Yes
	Chicago-Joliet-Naperville	7,737	1,037	8,340	839	No
	Dallas-Fort Worth-Arlington	6,056	877	5,677	854	No
	Miami-Fort Lauderdale-Pompano Beach	5,948	925	7,910	1,088	Yes
	San Francisco-Oakland-Santa Clara	5,875	797	7,399	966	Yes

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

[11] Excludes movers from abroad and intermetropolitan moves.

Table 7: Selected CBSAs with Among the Highest Creative Class Migration by Analytic Knowledge Base 2006-2008 & 2009-2011

		2006-2008		**2009-2011**		Significantly Different
From CBSA	To CBSA	Estimate	MOE	Estimate	MOE	
Washington-Arlington-Alexandria	Baltimore-Towson	1,411	360	1,379	456	No
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	1,312	355	1,541	404	No
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	1,303	314	2,176	398	Yes
Baltimore-Towson	Washington-Arlington-Alexandria	985	337	852	284	No
Philadelphia-Camden-Wilmington	New York-Northern New Jersey-Long Island	928	573	589	255	No
		2006-2008		**2009-2011**		Significantly Different
From CBSA	To CBSA	Estimate	MOE	Estimate	MOE	
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	1,303	314	2,176	398	Yes
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	1,312	355	1,541	404	No
Washington-Arlington-Alexandria	Baltimore-Towson	1,411	360	1,379	456	No
Baltimore-Towson	Washington-Arlington-Alexandria	985	337	852	284	No
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	728	232	739	272	No

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

Lines in RED are among selected flows for both 2006-2008 & 2009-2011.

Table 8: Selected CBSAs with Among the Highest Creative Class Migration by Synthetic Knowledge Base 2006-2008 & 2009-2011

		2006-2008		2009-2011		Significantly Different
From CBSA	To CBSA	Estimate	MOE	Estimate	MOE	
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	656	369	536	218	No
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	392	177	688	283	No
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	343	198	840	396	Yes
Detroit-Warren-Livonia	Seattle-Tacoma-Bellevue	319	212	0	115	Yes
New York-Northern New Jersey-Long Island	Philadelphia-Camden-Wilmington	309	200	330	280	No
		2006-2008		2009-2011		Significantly Different
From CBSA	To CBSA	Estimate	MOE	Estimate	MOE	
San Francisco-Oakland-Fremont	San Jose-Sunnyvale-Santa Clara	343	198	840	396	Yes
San Jose-Sunnyvale-Santa Clara	San Francisco-Oakland-Fremont	392	177	688	283	No
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	656	369	536	218	No
New York-Northern New Jersey-Long Island	Philadelphia-Camden-Wilmington	309	200	330	280	No
New York-Northern New Jersey-Long Island	Poughkeepsie-Newburgh-Middletown	78	57	257	232	No

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

Lines in RED are among selected flows for both 2006-2008 & 2009-2011.

Table 9: Selected CBSAs with Among the Highest Creative Class Migration by Symbolic Knowledge Base 2006-2008 & 2009-2011

		2006-2008		**2009-2011**		Significantly Different
From CBSA	To CBSA	Estimate	MOE	Estimate	MOE	
New York-Northern New Jersey-Long Island	Los Angeles-Long Beach-Santa Ana	780	321	1,090	399	No
Los Angeles-Long Beach-Santa Ana	New York-Northern New Jersey-Long Island	702	418	328	190	No
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	518	183	652	295	No
New York-Northern New Jersey-Long Island	Miami-Fort Lauderdale-Pompano Beach	460	211	98	83	Yes
Boston-Cambridge-Quincy	New York-Northern New Jersey-Long Island	450	246	98	95	Yes
		2006-2008		**2009-2011**		Significantly Different
From CBSA	To CBSA	Estimate	MOE	Estimate	MOE	
New York-Northern New Jersey-Long Island	Los Angeles-Long Beach-Santa Ana	780	321	1,090	399	No
Los Angeles-Long Beach-Santa Ana	Riverside-San Bernardino-Ontario	518	183	652	295	No
Philadelphia-Camden-Wilmington	New York-Northern New Jersey-Long Island	200	108	605	287	Yes
San Francisco-Oakland-Santa Clara	Los Angeles-Long Beach-Santa Ana	397	213	501	316	No
New York-Northern New Jersey-Long Island	San Francisco-Oakland-Fremont	111	66	368	253	No

Source: American Community Survey 2006-2008 and 2009-20113-year data. For more information, see http://www.census.gov/acs

Lines in RED are among selected flows for both 2006-2008 & 2009-2011.